Globalization and Income Inequality:
An Empirical Investigation across European Regions

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Part I

Introduction

Chapter 1

Introduction

1.1 Motivation

In the EU, public opinion on globalization and free trade is not very favorable. The Eurobarometer[1], a survey based on face-to-face interviews across all member states of the European Union, assesses attitudes toward globalization and shows three main findings.

- A majority thinks that globalization promotes economic growth but benefits only large companies and not citizens.
- 61% of respondents in the euro zone countries thinks that globalization increases inequality.
- In twenty-three member states (of twenty-seven), the relocation of companies to countries where labor is cheaper is the first thing that respondents associate with globalization.

In a nutshell, globalization, generally, and the terms *offshoring* and *outsourcing*, particularly, are associated with increasing inequality and the loss of jobs (Kirkeegaard [1]).

To date, the question of whether this perception is primarily a product of media hysteria and populist politics or is justified by economic facts remains open to debate. On the one hand, the first view is supported by authors who argue

[1]Eurobarometer Standard 69, Spring 2008

that offshoring is more of a political than an economic issue (e.g., Mankiw and Swagel [2]), while on the other hand, an alternate perspective (e.g., Krugman [3], Blinder [4]) suggests that there are substantial economic impacts.
The phenomenon of offshoring, defined as the relocation abroad of parts of the production process (either to an affiliated or unaffiliated firm), is clearly only one thread of the whole globalization story. Due the public sensitivity to foreign-induced job displacements, however, offshoring receives considerable attention and will also be at the core of this dissertation.

In my opinion, an improved knowledge of the correlations between globalization and income inequality is crucial to understanding public opinion and, consequently, the political response to globalization. Better empirical evidence in particular can help to bridge the communication gap (Mankiw and Swagel [2]) between economists and non-economists regarding the subsequent costs and benefits of globalization.

As a first step in this procedure, I try to shed some light on the available evidence about globalization, jobs and income distribution. The empirical evidence can be divided into two categories of studies.

- The first category directly assesses whether globalization has a significant impact on income inequality across countries.

- The second category focuses on the impact of globalization on labor market outcomes, largely by drawing conclusions based on industry-level evidence.

I begin with a selective review of the second line of research because on the one hand, evidence of the wage and employment effects of globalization are crucial to understanding the effects on income inequality, and on the other hand, the labor market implications dominate the thematic field.

1.2 Literature Review

1.2.1 Globalization and the Labor Market

The impact of globalization[2] on labor market outcomes has received a great deal of attention. Many of the theoretical and empirical contributions on the subject were motivated by the well-documented rise of wage inequality in the US and the apparent increase of the wage premium for highly skilled workers in most parts of the developed world (Katz and Autor [5], Acemoglu [6]).

Theoretical studies typically emphasize two closely related explanations of how globalization affects wages and employment.

The first explanation - the classical textbook story - argues that trade in countries with very low wages, such as China or India, worsens the labor market outcomes of low-skilled workers in the first world. This argument, in accordance with the Stolper-Samuelson theorem, predicts that if trade with labor-abundant countries reduces the relative price of labor-intensive goods, then this should reduce the real wages of less skilled workers, both in absolute terms and relative to other workers.

The second line of argumentation claims - expressed here in somewhat simplified terms - that the restructuring of production processes combined with the offshoring of low-skilled, labor-intensive production shifts the relative skilled labor demand outward. This results in a rise in relative wages and in the employment shares of highly skilled workers, which is identical to the effect of skill-biased technological change.
This explanation (and especially, its focus on offshoring) aimed to address the difficulty of using traditional trade theory to explain the simultaneous rise of the relative wages of highly skilled workers in developed countries and less developed countries, an outcome that stands in contrast with the prediction of the Stolper-Samuelson theorem (Feenstra [7]).

[2] To clarify terminology: in the following, the term globalization refers to the trade-related components (including offshoring) of the phenomenon and leaves aside any further financial, social and cultural aspects. (See the introduction of chapter 3 for a more detailed discussion).

Empirically, a widespread consensus holds that technological progress and, to a lesser extent, the offshoring of low-skilled labor-intensive production were responsible for the outward shift of the relative skilled labor demand that resulted in a rise of the relative wages (and employment shares) of the skilled workers. Several empirical studies based on industry-level panel data found that offshoring and high-technology capital contributed significantly to the increase of the highly skilled labor share of the total wage bill and total employment. The respective empirical inquiries were based mostly on the influential contributions of Feenstra and Hanson [8] and [9]. For a detailed literature review on the impact of offshoring and multinationals on the labor market, see Crino [10].
As noted previously, most of these studies were driven by the empirical evidence of rising wage inequality in the US, but with regard to Europe, the data show a different picture. Most importantly, there is no evidence pointing to a systematic increase of wage inequality across Europe (Acemoglu [11]). This seems puzzling, as skill-biased technological change did not stop at the European borders; Berman et al. [12] documented the pervasiveness of skill-biased technological change throughout most of the developed world. Although differences in the behavior of relative supplies of skilled workers in the U.S. and continental Europe can explain part of the disparity (see (Acemoglu [11]), the most likely explanation is that the more rigid labor market and European wage-setting institutions prevented wage inequality from increasing. Krugman [13] made this point more than a decade ago:" *The European unemployment problem and the U.S. inequality problem are two sides of the same coin...*".
This argument gains support from a glance at the European unemployment data. Unemployment rates in the EU-15 remained persistently high over the '90s even though they were, on average, lower in 2000 than in 1990. The EU-15 standardized unemployment rate was 8.1% in 1990, rose to 10.1% in 1995 and declined to 7.7% in 2000.[3]

Some attempts have been made to quantify the direct job losses due to the offshoring of production. The problem with those measurement attempts is that all the available data sources have significant shortcomings. That said,

[3]Source: OECD Employment Outlook - Boosting Jobs and Incomes OECD 2006

the numbers provide evidence that offshoring plays only a minor role in job displacement.

- The `European Restructuring Monitor`, a data source based on the media-coverage of job displacements, indicates that the number of job losses through offshoring activities is small compared to overall job turnover (Kirkegaard [1]).

- Kletzer [14] evaluated the displacement statistics for US manufacturing. As a main conclusion, he stated: *"Import-related job loss is a sizeable share of US manufacturing job loss, and a much smaller share of economy-wide job loss. The probability of re-employment is low for import-competing displaced workers (relative to non-manufacturing workers), with sizeable earnings losses on average."*

Both studies on job displacement point to the same conclusion, i.e., offshoring is presumably only responsible for a very small proportion of all displaced workers.

In summary, progress in information and communication technology and offshoring activities has contributed to the shift of the relative skilled labor demand in most parts of the developed world, but the outcome of this demand shift varied strongly between countries because it depends on labor market and wage-setting flexibility, which are both quite heterogeneously developed across Europe. On average, the more rigid labor market in Europe prevented a systematic increase in wage inequality compared to the US. As a consequence, however, globalization and technological change were accompanied by an increase in unemployment for the relatively unskilled population.

1.2.2 Globalization and Income Inequality

Given all of the industry-level evidence regarding globalization and the labor market that led to the conclusions discussed above, was there any measurable impact on income inequality? The following section reviews the available literature addressing that question.

Despite the fact that the time from the mid 80s to the end of the twentieth cen-

tury has been a period of massive economic integration in Europe, the data[4] This apparent lack of co-movement seems to be reflected in the literature. The available empirical studies do not give satisfactory answers as to whether or how globalization is correlated with income inequality.
Overall, only a surprisingly small number of econometric studies focused at all on the core issue of whether globalization had a measurable effect on income inequality. The explanation for this, presumably, is the complexity of the question, which makes it difficult to identify robust correlations and to deliver clear predictions. In particular, the identification of secondary effects (such as those of offshoring or of technological progress) is challenging because inequality measures like the Gini coefficient conceal divergent movements at different points in the income distribution.

Despite these considerable difficulties, a review of the available evidence may still shed some light on the issue. The main obstacle in the way of a comparison of the results is that the empirical specifications, the inequality and globalization measures, the sample selection and also the chosen time periods vary substantially between the available studies. Therefore, table 1.1 summarizes several selected studies with common characteristics. All of these studies include a trade-based globalization measure in their explanatory variables, although their main research focus was not necessarily on globalization. The sign of the respective globalization coefficient is indicated (if significant) in the last column of table 1.1.

Alderson and Nielson [15] and Gustafsson and Johansson [16] both find a positive effect of the southern import penetration ratio on inequality during a similar time period. This is not confirmed by the studies of Mahler [17] and Wallerstein [18], who find a negative sign for trade on inequality.
Studies that go beyond the OECD and include developing countries as well - Dreher [19], Edwards [20] and Jaumotte et al. [21] - find either no impact or a negative sign on trade variables. In addition, Jaumotte et al.[21], the most recent study, included a measure of information and communication technology

[4] A detailed documentation of European household inequality will be given in chapter 2 shows only very limited movement in inequality.

(ICT) that was found to be positively related to inequality, consistent with the predictions of skill-biased technological change.

Table 1.1: Literature Review: Globalization and Household Income Inequality

Study	**Sample**(1)	**Time**	**Method**(2)	**Inequality**(3)	**Indicator**(4)	**Sign**(5)
Jaumotte et al. [21]	Broad	1985 - 2000	FEM, IV	Gini	Export/Import	(-)/(-)
Alderson & Nielson [15]	OECD	1967 - 1992	REM	Gini	Import	(+)
Dreher [19]	OECD, Broad	1970 - 2000	GMM (LDV)	Gini	Glob. Index	(ns)
Mahler [17]	OECD	1980 - 1995	OLS (LDV)	P90P10 / Wage Ineq.	Trade	(-) / (ns)
Gustafsson & Johansson [16]	OECD	1966 - 1994	FEM, REM	Gini, MLD, Theil	Import	(+)
Edwards [20]	Broad	1970 - 1980	FD	Gini	Trade Reform	(ns)
Wallerstein [18]	OECD	1980 - 1992	GLS, FEM	P90P10	Trade	(-)

(1) Broad = OECD and developing countries
(2) FEM = Fixed Effect Method, IV = Instrumental Variable, REM = Random Effect Model, GMM = Generalized Method of Moments, FD = First Differences
OLS = Ordinary Least Squares, (LDV) = A lagged dependent variable was included
(3) Inequality measures are based on disposable household income with the exception of Mahler (2001), who applies as well wage income.
MLD = Mean Logarithmic Deviation, P90P10 = Ratio of the 90th to the 10th Percentile
(4) ”Export” = Exports to GDP, ”Import” = Imports to GDP, ”Trade” = Exports and Imports to GDP, ”Glob. Index” = Economic Globalization Index
”Trade Reform” = Dummy variable indicating a period of trade liberalization
(5) Refers to the sign of the coefficient of the respective indicator, i.e., (+) = significant positive sign, (-) = significant negative sign, (ns) = not significant

Put gently, the available empirical evidence is not conclusive on the link between globalization and income inequality. In other words, the results of the studies point to diametrically divergent conclusions.

1.3 The Initial Situation

Most research has focused on identifying the various channels through which globalization affects inequality but has neglected the core question: did globalization make the income distribution more unequal?
The preceding literature review revealed severe discrepancies between the empirical findings on the subject, and those discrepancies are difficult to explain. I want to emphasize two important aspects of the relationship between globalization and the income distribution that were neglected in the studies outlined above:
(i) the impact of the different welfare and redistribution systems and (ii) the regional implications of globalization.

(i) The first issue concerns the fact that in a majority of studies, the applied inequality measures were based on disposable household income. This is not appropriate to identify the effects of globalization on the income distribution because redistribution by transfers and taxes covers up underlying impacts on the distribution of market income. Hence, we may have a partial explanation of the unstable sign of globalization coefficients across studies. To substantiate this argument consider an example given by Atkinson and Brandolini [22]: Imagine a simple (closed) economy with skilled and unskilled workers, where globalization is expected to increase the relative demand for skilled labor. In such a setting, globalization is expected to increase market income inequality due to unemployment or rising wage dispersion. However, even in such a simple world, the interaction with redistribution makes the impact of globalization on disposable income inequality - measured by the Gini coefficient - so complicated that predictions become very difficult.
To gain more reliable insights on the impact of globalization on inequality, the distribution of income before transfers and tax payments should

be the starting point of any analysis based on household data.

(ii) Second, and presumably equally important to improving the empirical results on the topic, in all of the cited studies, regional differences within larger countries are neglected. Such intra-country disparities are sizable in terms of both inequality and globalization. Intra-regional inequality accounts for three quarters of the overall EU-25 inequality in 2000, while the remaining part is mostly attributable to the gap between the EU-15 and the CEE (Central and Eastern Europe) countries (Hoffmeister [23]). Similarly, Mahler [24]) documents substantial regional variation in inequality within countries for the year 1995.

The idea that globalization intensity in Europe is strongly region specific is supported by manufacturing data. Throughout Europe, there is a substantial degree of regional economic specialization and concentration of manufacturing industries (Hallet [25]). This, in turn, is relevant to globalization intensities because trade and offshoring are closely interlinked with the manufacturing sector. Expressed in simplified terms, a region without car production is not directly affected by car imports or exports. In other words, the degree of regional specialization in manufacturing industries is responsible for the degree of globalization variability between regions within the same country. If globalization is analyzed on the level of the nation state, these regional disparities will be averaged out and lost.

In a nutshell, an analysis of the effects of globalization on inequality in Europe with consideration of the different transfer and tax regimes and of the regional disparities may result in substantial gains in accuracy.

1.4 Aim of the Analysis

The available empirical evidence on the link between globalization, technology and income inequality is unsatisfactory. This dissertation aims to improve the understanding of the relationship between those phenomena by reassessing the impact of globalization on income inequality. The scope of the analysis will be narrowed down to Western Europe, a reasonably homogeneous area that has undergone massive economic integration during the last twenty years.

The main unit of analysis will be *European regions*, with the regional boundaries following the official "nomenclature of the unités territoires statistiques" (NUTS) of the European Union. Such an approach, however, postulates the availability of consistent regional data including inequality and globalization measures. The Eurostat Regio-Database provides a good deal of regional data across western European countries, but there are neither data on intra-regional inequality nor on regional globalization intensities available.
As a first step, one of the goals and main contributions of this dissertation, then, will be to resolve this deficit, i.e., to compile a database of intra-regional inequality measures and feasible indicators of regional globalization intensity.

In a second step, this study aims to do a thorough econometric assessment of the relationship between globalization and inequality. The goal is to show if and how model specifications (like the selection of the dependent and independent variables) influence the empirical findings. Given the negative public perception, special attention will be paid to the phenomenon of offshoring with respect to manufacturing and, within the limits of the available data, to services.

A further aim of the analysis is to improve the reliability of the findings by applying inequality measures based on *income before transfer payments*.[5] Thereby, it is possible to analyze the extent to which the social state mitigates the impact of globalization on income distribution.

In view of the unstable results of previous empirical contributions, this study proposes the use of meta-analysis techniques as a tool to do a more systematic econometric evaluation. A meta-analysis of a great deal of (self-generated) regression results for several globalization indicators, inequality measures and other model specifications will be conducted. In face of concerns about the reliability of the regional data and possible spurious findings, the meta-analysis will be the principal component of the econometric evaluation and serves as well to specify a regression model as a benchmark for further estimations.

[5]Note that tax effects will not be taken into account due to missing data.

In my opinion, the proposed procedure can contribute significantly to the search for better answers to one of the core questions of the globalization discussion.

1.5 Structure of the Dissertation

The remainder of this dissertation is organized as follows.

PART II discusses the main data - intra-regional inequality and regional globalization and technology measures - for the econometric analysis.
Chapter 2 documents the evaluation of the LIS regarding intra-regional inequality measures and gives a descriptive evaluation of income inequality within European NUTS-1 regions.
Chapter 3 describes the construction of regional globalization and technology indicators using a top-down approach. Four differential measures of regional trade and offshoring and a measure for progress in ICT are calculated. Levels and trends of these indicators are described for the period 1985 - 2000.

PART III presents the econometric investigation.
Chapter 4 describes and motivates the econometric procedure and documents the construction of the meta-database. The database is specified based on a broad spectrum of possible test equations to subsequently analyze most thoroughly the relationship between globalization and inequality and to identify robust model specifications.
Chapter 5 first reports the findings of the meta-analysis based on the descriptive evaluation of the coefficients of interest and on meta-regressions. In the second part of the chapter, a regression model is specified (based on the previous findings) as a benchmark to conduct several robustness tests and to shed some light on the interaction between structural change and offshoring.
Chapter 6 complements the discussion by showing some preliminary evidence on the relationship between service offshoring and regional unemployment rates.
Chapter 7 summarizes and concludes.

Part II

Main Data

Chapter 2

Intra-Regional Inequality

2.1 Introduction

As outlined in the previous chapter, the impact of globalization on income distribution will be analyzed on a regional level, but this presupposes consistent data of intra-regional inequality measures across regions and time.

This chapter describes the availability of regional inequality measures and documents the development of household income inequality within European NUTS-1 regions. All measures are calculated for disposable as well as net (after-tax) market income to document the effect of transfer-based redistribution on inequality. The data source for this project is the Luxembourg Income Study database (LIS). The LIS is a collection of various household surveys that are harmonized ex post to create an internationally comparable data set (see Gottschalk and Smeeding [26] for a detailed description of the LIS). The earliest data available are from the late 1970s. The LIS allows a spatial exploitation of inequality within countries over time for many European countries (Mahler [24], Jesuit [27]). Regional evaluation of the surveys is possible consistently from the mid-eighties for the EU-4 countries Germany, the UK, France and Italy.

The chapter is structured as follows.

- The first part presents some stylized facts about inequality in Europe and documents what is known about inequality within and between European regions.

- The second part focuses on technical and methodological measurement aspects and discusses the availability and quality of regional data.
- The third part describes intra-regional inequality levels and subsequent change over time for the period 1985 to 2000 on NUTS level 1
- The final part briefly documents the decomposition into within/between inequality components for the EU-12 regions and describes how median income developed relative to GDP per capita.

2.2 Did Inequality Increase? A Review

Household Inequality in Europe since 1985

What are the stylized facts about income inequality in Europe? The pattern of European household income inequality has been described in various empirical papers. The following is based primarily on a comprehensive review defining stylized facts for the period of the 1980s and early 1990s given in Gottschalk and Smeeding [26] for earning[1] and disposable income inequality. An extension of the description to the end of the century can be found in a more recent contribution of Foerster and d'Ercole [28].

The main facts about *inequality levels* are the following.

- There are wide differences across European countries in the level of market and disposable income inequality, but disposable income is more equally distributed than market income.
- The inequality level of disposable income is highly correlated with spending on social security, with Britain and the Mediterranean states at the top of inequality rankings and France and the Nordic states at the bottom.

The main facts about *inequality trends* are the following.

- There was no common trend apparent across Europe.
- From the mid-80s to the mid-90s, inequality and, especially, inequality in the upper part of the income distribution increased in most OECD countries. In the late, however, '90s inequality remained constant!
- The rise in income inequality during the early '90s was less pronounced for disposable than for market income.

Some key figures[2], including disposable income Gini coefficients for all countries and surveys, are summarized in table 2.1. The data are sorted by year to allow a quick overview. An increase of the Gini is observable for Belgium, Finland and United Kingdom, while France, Austria and Denmark show decreasing Gini coefficients over time. In Germany and Italy, inequality evolved less uniformly over time.

[1] Earnings and self-employment income

[2] available on the LIS homepage www.lisproject.org

Table 2.1: LIS Key Figures: Disposable Income Gini Coefficients

	Survey Year$^{(1)}$			
COUNTRIES	1985	1990	1995	2000
United Kingdom	0.303	0.336	0.339	0.343
Germany	0.268	0.257	0.273	0.275
France	0.292	0.287	0.288	0.278
Italy	0.332	0.29	0.338	0.333
Belgium	0.227	0.232	0.266	0.28
Finland	0.209	0.21	0.217	0.247
Greece	*	*	0.349	0.333
Sweden	0.218	0.229	0.221	0.252
Spain	*	0.303	0.353	0.336
Denmark	0.254	0.236	0.218	0.225
Luxembourg	0.237	0.239	0.235	0.26
Austria	0.28	*	0.277	0.257
Ireland	0.313	0.336	*	0.328

* no data available, (1) for the exact survey years see table 2.2

In addition, some papers have estimated inequality in Europe on the supranational European level. The first attempt to calculate overall inequality in Europe (more precisely for the eleven founding members of the monetary union) was done by Beblo and Knaus [29]. They estimated a Theil index for Euroland and calculated the within- and between-country components. The overall Theil index was about 0.18 in 1995 (approximately the level of Italy), and between-country inequality contributed around 10 percent to disposable income inequality. However, for net-market income inequality the between-country components contributed only around 3.5 percent to overall inequality because the rich countries redistribute more than poorer countries and thereby, increased between inequality.
Brandolini [30] extended the focus to the enlarged European Union by including data from newly joined member states. He found that the Gini coefficient for purchasing power parity adjusted income in the EU-25 is around 0.32, while for the EU-15 and the Euro area, it is around 0.29. In his article, there is no decomposition done into within and between components.

With regard to the regional level - i.e., analyzing intra- or interregional inequality, the available data are less systematically evaluated.

Mahler [24] calculated subnational inequality measures for the LIS waves three and four (to the mid-90s). He found substantial regional variation in within-country inequality. Similarly, Hoffmeister [23] decomposed the inequality of the EU-25 to the regional level. He showed that the intra-regional inequality accounts for three quarters of the overall inequality, while the remaining part is mostly attributable to the gap between the EU-15 and the CEE (Central Eastern Europe) countries. Both between-regional and between-country inequality are found to be only marginal important in determining overall inequality.

In summary, the main findings of this review are the following.

- Disposable income inequality was - with some exceptions - rather stable over time.
- Social security spending compensated for a rise in market income inequality.
- In the EU-15, the main part of inequality comes from within-regional inequality, whereas between-regional and between-country inequality are less important.

2.3 Data and Methods

2.3.1 Availability

The evidence in the preceding section comes mostly from two sources. The data are either drawn from the Luxembourg Income Study (LIS) or from the European Community Household Panel (ECHP). While in the ECHP, surveys are more comparable and availability is more limited than is the case for the LIS, which provides a comparable database across Europe. As mentioned in the introduction, the LIS is a database that consists of surveys that are ex post harmonized to improve comparability (see Atkinson [31]) Table 2.2 lists the year of the applied surveys and the availability of NUTS level 1 data for selected countries. Following the LIS terminology, the surveys correspond to four *waves*:[3] Wave II corresponds roughly to the year 1985, wave III to the year

[3]Wave I does not contain information on the regional composition.

1990, wave IV to 1995 and finally, wave V to the year 2000. For about half of the countries, data are only available since wave IV. Therefore, I distinguish in the data documentation and the remaining part of this dissertation between the full and the '*EU-4*' (balanced) subsample including western Germany, the United Kingdom, France and Italy.

Table 2.2: Exact Survey Years by Country and Wave and Number of Available NUTS-1 Regions

	Wave				No. of NUTS1
	II	III	IV	V	Regions
Germany (West)	1984	1989	1994	2000	10 (1)
Germany (East)			1994	2000	6 (2)
United Kingdom	1986	1991	1994(3)	1999	12 (4)
France	1984	1989	1994	2000	7
Italy	1987	1991	1995	2000	5
Belgium	1985	1988	1995	2000	3
Sweden			1995	2000	1
Finland	1987	1991	1995	2000	2 (5)
Spain			1995	2000	7
Greece			1995	2000	4
Austria			1995	2000	3
Luxembourg	1985	1991	1995	2000	1
Ireland			1995	2000	1
Denmark	1987	1992	1995	2000	1

(1) Rhineland-Pfalz and Saarland together
(2) Including East Berlin
(3) The UK data come from two different surveys: the Family Expenditure Survey (FES) (UK86, UK91, UK95) and the Family Resources Survey (FRS) (UK94, UK99). I use the UK94 survey (FRS) because it relies on much higher number of observations and seems to be more reliable on the regional level.
(4) Classification is based on NUTS 95.
(5) NUTS 1 region "Aland" is excluded in the following.

Many LIS surveys have a sub-national dimension. The regional decomposition in most cases follows the NUTS[4] classification.[6] In several surveys, data on NUTS level 2 or even on level 3 are also available. Nevertheless, the regional analysis is done on level 1. NUTS 2 data are aggregated when necessary to the corresponding NUTS 1 units.

The restriction on NUTS 1 and the decision not to entangle the two regional classifications has two advantages.

- First, the sample becomes more homogeneous in terms of economic and population size, and the economic size of the region is much bigger on average. This reduces the possible problem of inter-linkages between neighboring regions. In small regions, problems arise from commuting - which can have a substantial impact on the average income - and from industry inter-linkages across regional borders. On NUTS level 1, at least, the problems of commuting will be reduced, even though they may remain an issue in city[7] regions (Boldrin and Canova [32])

- Secondly, the reliability of the inequality measures will improve because of the increase in the number of observations per region, as will be discussed in the next section.

In summary, the sample gets smaller but more homogeneous, and the reliability of the estimated inequality measures increases.
It is important to note that some of the smaller (or less populated) countries are counted as one NUTS 1 region. Hence, I am in fact using country level data for Luxembourg, Finland, Sweden, Denmark and Ireland. The Netherlands, for which there is only a spatial differentiation in wave four, and Portugal, which lacks regional data, are excluded from the analysis.

[4]The economic territory of the EU is divided into 271 NUTS 2 and 97 NUTS 1 regions. The NUTS nomenclature is based primarily on the institutional divisions currently in force in the member states (normative criteria) but does not necessarily correspond to the administrative units. The regions differ strongly in terms of economic size, area and population [5]. The average size of a NUTS 1 region is between three and seven million inhabitants. The largest NUTS 1 region is continental Finland with over $300'000 km^2$, while the NUTS region with the highest population is Nordrhin-Westfalia with a population of eighteen million people.

[6]See also Jesuit [27] for a description of regional availability.

[7]Bremen, Hamburg, Berlin, London and (in parts) Paris

2.3.2 Data Quality

There is some statistical uncertainty about point estimates in survey data. The degree of this uncertainty depends to a large part on the sample size of the underlying survey.
The surveys listed in table 2.2 contain a widely varying number of observations. Moran [33] showed with bootstrap procedures that the degree of uncertainty of LIS inequality measures is small, i.e., confidence intervals are in a range from plus/minus 1 to 3 percent. Regional inequality measures, however, are less precise than country level estimates due to the reduced sample size.

Table 2.3 gives an indication of the approximative quality of the regional measures. The regions are classified here into four categories - weak, sufficient, good and excellent - subject to the respective number of observations.
For Italy[8], France, Spain, Greece and Austria, the sample size of the surveys is high enough to allow a decomposition without loss of reliability. For several surveys, however, the quality seems problematic. The regional decomposition in Germany, in particular, is based on relatively small sample sizes and contains a large number of regions. It is unsurprising, therefore, that the lowest reliability is found for Bremen and Hamburg where inequality measures are based in some surveys on fewer than 100 observations. The same holds partly for the UK, where some regions also fall into a problematic data quality range.
The insufficient sample size for a part of the surveys precludes any further decomposition, even though it would have been preferable to restrict the analysis to the incomes of the working age population.

2.3.3 Data Treatment

The calculation of inequality measures requires some adjustments. Accordingly, I follow the recommendations outlined in Atkinson [31]. In a first step, household income is transformed into individual equivalent income. To correct for economies of scale in consumption, as households vary in size, an equivalence scale has to be applied. The income is divided by the square root of the

[8]The available NUTS 2 decomposition is unreliable for several regions. The same holds for France.

Table 2.3: Quality Indicator based on the Number of Observations per Region

Name	NUTS	Country	1985	1990	1995	2000
Berlin (west)	de3	DE	*	-	**	**
Schleswig-Holstein	def	DE	-	-	-	*
Hamburg	de6	DE	-	-	-	-
Niedersachsen	de9	DE	**	*	**	***
Bremen	de5	DE	-	-	-	-
Nordrhein-Westfalen	dea	DE	***	***	***	***
Hessen	de7	DE	**	*	*	**
Rheinland-Pfalz + Saarland	deb+dec	DE	*	*	*	**
Baden-Wuerttemberg	de1	DE	***	**	***	***
Bayern	de2	DE	***	**	***	***
North & Cumbria	ukc + ukd1	UK	*	*	*	***
Yorks & Humberside	uke	UK	**	**	**	***
North West	ukd-ukd1	UK	***	**	**	***
East Midlands	ukf	UK	*	**	*	***
West Midlands	ukg	UK	**	**	**	***
East Anglia	ukh1	UK	*	*	*	***
Greater London	uki	UK	**	**	**	***
South East exc London	ukj+ukh2+ukh3	UK	***	***	***	***
South West	ukk	UK	**	**	**	***
Wales	ukl	UK	*	*	*	***
Scotland	ukm	UK	**	**	**	***
Nord Ovest	itc	IT	***	***	***	***
Nord Est	itd	IT	***	***	***	***
Centro (IT)	ite	IT	***	***	***	***
Sud (IT)	itf	IT	***	***	***	***
Isole (IT)	itg	IT	***	***	***	***
Île de France	fr1	FR	***	***	***	***
Bassin Parisien	fr2	FR	***	***	***	***
Nord - Pas-de-Calais	fr3	FR	***	**	**	**
Est	fr4	FR	***	***	***	***
Ouest	fr5	FR	***	***	***	***
Sud-Ouest	fr6	FR	***	***	***	***
Centre-Est	fr7	FR	***	***	***	***
Méditerranée	fr8	FR	***	***	***	***
Flandern	be2	BE	***	***	***	***
Wallonia	be3	BE	***	***	***	***
Brussel	be1	BE	**	-	*	*
Noroeste	es1	ES			***	**
Noreste	es2	ES			***	**
Comunidad de Madrid	es3	ES			**	*
Centro (ES)	es4	ES			***	***
Este	es5	ES			***	***
Sur	es6	ES			***	***
Canarias (ES)	es7	ES			*	*
Voreia Ellada	gr1	GR			***	***
Kentriki Ellada	gr2	GR			***	***
Attiki	gr3	GR			***	***
Nisia Aigaiou, Kriti	gr4	GR			**	**
Finland	Fi	FI	***	***	***	***
Denmark	Den	DEN	***	***	***	***
Luxembourg	Lux	LU	***	***	***	***
Ireland	Ir	IE	***	***	***	***
Austria Ost	Aus1	AT			***	***
Austria Sd	Aus2	AT			***	**
Austria West	Aus3	AT			***	***
Sweden	Swe	SE	***	***	***	***
Mecklenburg-Vorpommern	de8	DE			-	*
Brandenburg	de4	DE			*	*
Sachsen-Anhalt	dee	DE			*	*
Thüringen	deg	DE			*	*
Sachsen	ded	DE			**	***

Legend: (-) < 200 obs., (*) < 500 obs., (**) < 800 obs., (***) > 800 obs.

household size, and subsequently, the households are weighted by the number of members. As shown by Atkinson [31] this equivalization procedure is an approximation of the OECD[9] equivalence scales and is commonly applied. Note that the choice of the equivalence scale can have a significant impact on the distribution of income. The economies of scale of consumption are not the same everywhere and depend on the income level of the region or the household. See Brandolini [30] for a discussion of this problem and a description of some equivalence scales applied for EU countries.

In a second step, the data are top and bottom coded. This ensures comparability across surveys as top incomes are not reported for reasons of confidentiality. Household income is top-coded at 10 times the median of non-equivalized income, following the LIS recommendations. In addition, the data are bottom coded at 1% equivalized mean income (Gottschalk and Smeeding [26]), and negative incomes are dropped.

To compare absolute income values (deciles or average income) across Europe at a given point in time, two adjustments have to be made. First, because the survey data were not collected in an exact five year sequence, most of them have to be slightly adjusted. The respective income values are raised (or lowered) by the specific per capita Gross National Income (GNI) growth rates.
Second, the data have to be expressed in a common currency standard and corrected for inflation and price level Differences, as the LIS data are given in nominal terms in the respective national currency. To make the incomes Comparable, they are converted into year 2000 real purchasing power standard units (PPS)[10]. Brandolini [30] discusses the (quite substantial) impact of different deflators and methodical issues on price level adjustments. As the focus is on regions within developed countries, the price level differences are (on aggregate) much smaller than within a sample including developed and developing countries. Regional disparities within countries, e.g., in Italy between northern and southern regions, present an unsolved and substantial problem. Although there are substantial differences in regional price levels[11], no regional

[9]In the original OECD equivalence scale, every adult household member after the first is given a weight of 0.7, and children are weighted 0.5.

[10]All conversion rates were taken from the AMECO database.

[11]The cost of housing, in particular, varies substantially within countries (Joliffe [34])

PPS deflators are available.

2.3.4 Inequality Measurement

Disposable, Market and Net-Market Income

In light of the different welfare systems, inequality measurement in Europe should not limit itself to disposable income. Generally speaking, the optimal approach is to distinguish between the wage income distribution among workers and the market income distribution among the whole population in addition to the distribution of disposable income (Atkinson [22]). Unfortunately, it is not feasible to constrain inequality on wage incomes, given the limited sample size of some of the surveys. Additionally, market income is not available for all the surveys. Instead, the focus, in addition to that on disposable income, is on after-tax market income or (in short) *net-market income* among the whole population.

Market income (MI) is composed of wages and salaries, income from self-employment, property income and private sector pensions. Accordingly, the difference between market and disposable income (DPI) consists (roughly[12]) of social and private transfers and tax payments (including mandatory contributions for self-employed and employees). Hence,

$$DPI \cong MI + transfers - taxes$$

In the LIS, most surveys contain market income data[13], but unfortunately, the surveys report for several countries[14] only after-tax incomes. Therefore, only *net-market income* can be evaluated in those countries.

However, making no distinction between market income and net-market income results in a substantial measurement error. Therefore, I restrict the analysis on net-market income to get a homogeneous inequality sample.

[12]neglecting 'other cash income'

[13]The following surveys contain market income data: Germany (de84, de89, de94, de00), France (fr84, fr89, fr94), UK (uk86, uk91, uk95, uk99), BE (be92, be97), FI (fi87, fi91, fi95, fi00) and DK (dk95, dk00), SE (se95, se00).

[14]Italy, Belgium, Spain, Austria, Greece and France

In the following, *net-market income* will sometimes be abbreviated as *MI-net* income.

The calculation is done by subtracting taxes from market income and is (roughly) equivalent to disposable income without transfers:

$$\textit{MI-net} \equiv MI - taxes \cong DPI - transfers$$

However, there is one problem with this transformation. The impact of transfer payments will be overstated because transfers are also subject to taxes. To mitigate the issue, *MI-net* is set equal to the original MI value if *MI-net* < 0 due to taxes on transfers.

There are two features of net-market income that have to be emphasized to correctly interpret the inequality levels and also the subsequent application in the econometric analysis.
First, the two biggest sources of transfers are unemployment compensation and public pensions (although market income already includes private sector pension). Hence, the survey sample underlying net-market income inequality includes a substantial number of people with zero income.
Second, taxes, like transfers, have a redistributive effect on inequality that is not taken into account. Mahler and Jesuit [35] calculated the redistributive contributions of taxes and transfers on the Gini. (Thus, they excluded all net-market income surveys from their analysis.) They point out that taxes have a much smaller impact on inequality than transfers, even though the share of actual redistribution by taxes varies strongly between countries. According to their calculation, the relative share of taxes in overall fiscal redistribution [15] was, on average, around 25%, but obviously, the relative impact of taxes on inequality depends strongly on the selected inequality measure, i.e., on the respective sensitivity to changes in upper incomes.

However, it should be emphasized that inequality measures based on net-market income are the best feasible solution and accomplish the main purpose. Thus, the impact of globalization on inequality can be analyzed without the distortive influence of transfer-based redistribution across Europe.

[15] Measured as the difference between the disposable and the market income Gini coefficients

Inequality Measures

To document regional inequality, three measures with different properties are applied: the Gini coefficient, the mean logarithmic deviation (MLD) and the ratio of the 90th to the 50th percentile (P90P50).

The Gini coefficient serves as the main inequality measure in most applications due to its prominent status in the literature and its straightforward interpretation. However, because the Gini coefficient may conceal divergent movements at different points in the distribution, the mean logarithmic deviation (MLD) and P90P50 decile ratio are applied as additional inequality measures.
The MLD belongs to the family of entropy-based inequality indexes (see Cowell [36] for a survey of inequality measures). The MLD has the property of being a more bottom sensitive measure than the Gini. Furthermore, it allows for the decomposition of the overall inequality into within and between inequality terms. (I prefer the MLD over the closely related Theil index because it is preferable to assign equal weight to rich and poor regions in this research context.)
Note that as a bottom-sensitive measure, the MLD has a higher inter-regional variation because it is sensitive to the number of people with no or very low market income, which varies rather strongly between countries and regions. The higher standard deviations in the upcoming summary table 2.4 confirm this presumption, but note also that the higher variation (compared to the Gini) can be observed at the country level and for disposable income.
The ratio of the 90th to the 50th percentile (P90P50) completes the picture as a measure that is more sensitive to movements in the upper part of the income distribution. In contrast to the Gini and the MLD index, this decile ratio measure is not affected by the top coding problem because top-coded incomes do not reach as low as the 90th percentile. (Unfortunately, is not possible to capture the very top-incomes with LIS data, even though they had a large impact on the income distribution (Piketty [37]).
The net-market income Gini, MLD and P90P50 coefficients will be abbreviated in the further writing as M-Gini, M-MLD and M-P90P50.

2.4 Descriptive Evidence

2.4.1 Overview

As described in the previous section, the documentation of inequality within European regions is based on the *Gini*, *MLD* and *P90P50*. This section is organized into two parts as follows.

- The first part documents the overall sample characteristics; descriptive statistics and the within and between variation of the regional inequality sample are shown.
- The second part goes into more detail; levels and trends of intra-regional inequality are described using graphical representations whereby the focus is on the *Gini* as the most commonly used inequality measure.

Summary Statistics and Variance Analysis

Table 2.4 displays the sample averages[16] and standard deviations for the three inequality measures: *Gini*, *MLD* and *P90P50*. The statistics are displayed for disposable and net-market income at a given time.

As several countries are added to the sample in 1995, the values for the *balanced* sample, consisting of the EU-4 and Belgium, Denmark, Luxembourg and Finland (see table 2.2), are displayed in addition to the numbers of the full sample in parentheses.

The summary statistics show that inequality was rather stable over time on average. The data show a decline of inequality from wave two (1985) to wave three (1990), followed by an increase to wave four (1995) and a rather stable period to wave five (2000). This is in line with the stylized facts described at the beginning of the chapter. Note that the increase in inequality from 1990 to 1995 was not driven by the inclusion of additional regions.
All three inequality measures show a similar behavior, but the MLD in particular, as a bottom sensitive measure, reacts very strongly to the removal of

[16]These summary statistics are not overall measures of EU-15 (without Portugal and Netherlands) inequality and are therefore not fully in accordance with the stylized facts outlined at the beginning of the chapter.

Table 2.4: Summary Statistics

			II (1985)	III (1990)	IV (1995)	V (2000)
Gini	DPI	Mean	0.28	0.28	0.29 (0.29)	0.29 (0.29)
		St. Dev.	*0.03*	*0.03*	*0.04 (0.04)*	*0.03 (0.04)*
	MI-Net	Mean	0.44	0.43	0.45 (0.46)	0.46 (0.47)
		St. Dev.	*0.04*	*0.05*	*0.04 (0.05)*	*0.03 (0.04)*
Q90Q50	DPI	Mean	1.81	1.80	1.89 (1.89)	1.89 (1.91)
		St. Dev.	*0.15*	*0.19*	*0.20 (0.20)*	*0.19 (0.20)*
	MI-Net	Mean	2.10	2.12	2.24 (2.24)	2.27 (2.31)
		St. Dev.	*0.23*	*0.32*	*0.29 (0.28)*	*0.26 (0.28)*
MLD	DPI	Mean	0.17	0.15	0.16 (0.16)	0.15 (0.16)
		St. Dev.	*0.05*	*0.04*	*0.05 (0.05)*	*0.05 (0.05)*
	MI-Net	Mean	0.79	0.72	0.79 (0.80)	0.82 (0.84)
		St. Dev.	*0.16*	*0.20*	*0.14 (0.17)*	*0.14 (0.15)*

Balanced subsample values are in parentheses

transfer income.
Apart from the fact that the income distribution is much more unequal for net-market income, there is no significant difference observable in the trend for disposable and net-market income inequality.

The standard deviations show no evidence of regional convergence of (intra-regional) inequality. Interestingly, disposable income inequality has a higher coefficient of variation than does net-market inequality. This indicates that transfers do not smooth out inequality differences between regions or (and more specifically) between regions of different countries.

Variance analysis allows us to gain further insights into how transfers affect inequality. The analysis is based on the Gini coefficient to allow a comparison with country studies (but the results for the MLD are of comparable size). Country-level inequality data are usually rather stable over time, i.e., the between-group variation dominates the overall variation. Li et al. [38] show that the cross-country variance explains roughly 90% of the overall variation in the Deininger and Squire [39] inequality data set.

Table 2.5 displays the residual sum of squares (SS) and the respective shares of the between- and within-group (regions) variation. The sum of squares is calculated for the disposable (Gini) and net-market income (M-Gini) and for the full and the EU-4 sample.

Table 2.5: Analysis of Variance for Gini and M-Gini

	Full Sample				EU-4 Sample			
	Gini		M-Gini		Gini		M-Gini	
	SS	in (%)	SS	in (%)	SS	in (%)	SS	in (%)
Between-group	0.27	79	0.33	69	0.11	68	0.22	71
Within-group	0.06	21	0.15	31	0.05	32	0.09	29
Total	0.34	100	0.48	100	0.16	100	0.31	100

In the case of the Gini, 79% of the sample variance is between regional. The within-group variation contributes around 21% to the overall variance. For M-Gini, the share of between-regional variance is 69%, and the within-variance is around 31%. In the case of the EU-4 sub-sample, the between-regional variance contributes around 68% for Gini and 71% for M-Gini.

The between-group variation for disposable income is lower in the EU-4 (68%) than in the full sample (79%), while it remains essentially equivalent for net-market income (69% and 71%).

This outcome is confirmed by the within- and between-group sample standard deviations displayed in table 2.6. Transfer payments do not reduce the between standard deviation of the full sample, but in contrast, in the EU-4

Table 2.6: Within- and Between-Group Standard Deviations for the Gini and M-Gini Samples

	Full Sample		EU-4 Sample	
Standard Deviation	Gini	M-Gini	Gini	M-Gini
Between-group	0.03	0.03	0.02	0.04
Within-group	0.01	0.02	0.01	0.02
Total	0.04	0.04	0.03	0.047

sample, the between standard deviation falls strongly from 0.04 to 0.02. Hence, transfers reduce differences in inequality between the regions in the EU-4 but not the between variation in the full sample. This is not surprising, as the full sample includes, in addition to the EU-4, several countries that have very different degrees of transfer-based redistribution, i.e., Greece, Spain and the Nordic countries.

The within-group standard deviations are reduced strongly by transfers in the full sample as well as in the EU-4 sample.

To summarize, the two main findings of this section are as follows.

- The variation of intra-regional inequality levels - measured by the standard deviation - remained constant, i.e., there was no sign of a convergence of regional inequality levels.
- Transfer payments reduce the within-group variation. Furthermore, they are found to reduce regional inequality disparities within the EU-4, but not within the full sample.

Unemployment and Net-Market Income

There are three groups of transfer payments: unemployment compensation, public pensions and other transfers (disability pay, child allowances, etc.). Mahler [35] finds for a broad sample of LIS surveys that the first two compensations constitute about two thirds of all social transfers and that half of redistribution through transfers is due to retirement pensions.

The net-market inequality measures are surely correlated to regional unemployment rates and possibly to the regional age structure as well. Table 2.7 lists the Spearman's correlation coefficients between the inequality measures separately for DPI and MI-net, regional unemployment rates (UNEMP) and the share of the population aged over 65 (AGE).

Overall, the figures show that the correlation between disposable and net-market income inequality is higher for measures that are less bottom sensitive. Furthermore, the P90P50 (ratio of the ninetieth percentile to the median) is more strongly correlated to the Gini coefficient than to the more bottom-sensitive MLD. Unsurprisingly, unemployment is much more strongly corre-

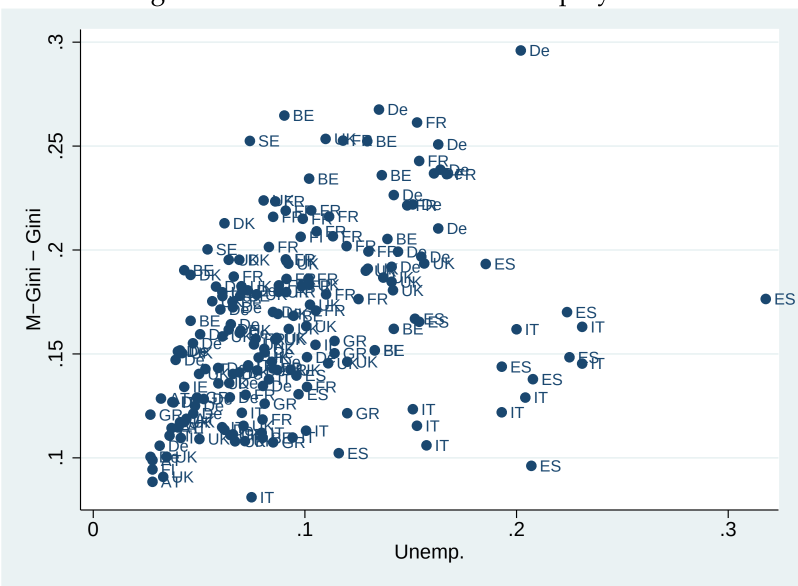
Table 2.7: Spearman's Rank Correlations

	Gini	M-Gini	MLD	M-MLD	P90P50	M-P90P50	UNEMP	AGE
Gini	1							
M-Gini	0.51*	1						
MLD	0.87*	0.49*	1					
M-MLD	0.31*	0.88*	0.36*	1				
P90P50	0.87*	0.53*	0.79*	0.31*	1			
M-P90P50	0.62*	0.80*	0.55*	0.60*	0.71*	1		
UNEMP	0.09	0.49*	0.22*	0.52*	0.22*	0.42*	1	
AGE	-0.01	0.02	0.01	0.07	-0.04	-0.01	-0.14	1

lated to measures based on net-market income than to those based on disposable income. Note as well that the share of the population aged over 65 is not correlated to inequality. Given the number of unemployed, however, the correlation between net-market inequality and unemployment seems rather low.

A scatter plot (figure 2.1) shows that the correlation between unemployment and the degree of effective redistribution by transfers (measured as the difference between M-Gini and (DPI) Gini) is reduced by a group of outliers. These are, on the one hand, several Spanish regions and on the other hand,

Figure 2.1: Redistribution and Unemployment



the two regions of the Mezzogiorno where high unemployment rates are not accompanied by high degrees of redistribution.

2.4.2 Level and Trends of Intra-regional Inequality

The goal in the following is to document the heterogeneity of inequality levels across regions and over time.

Inequality Levels: How Large are the Differences between Regions?

Let me start with the tails of the regional inequality distribution. This subsection documents the gap between the regions with the lowest and highest inequality values.

Table 2.8 summarizes the five regions with highest and lowest Gini coefficients for 1995 and 2000. As expected from country-level data, the highest levels of disposable income inequality are measured in UK regions and in regions around the Mediterranean Sea. The southern regions of Italy, Spain and *Voreia Ellada* Greece, in general, all display high levels of inequality.

In contrast, the lowest levels of inequality can be found in the Nordic countries and, perhaps surprisingly, in some eastern German regions. As an interesting example, *Sachsen-Anhalt* has one of the highest net-market but one of the lowest disposable income inequality levels. A plausible explanation would be the lack of high incomes combined with high levels of unemployment. *Sachsen-Anhalt* also has one of the lowest P90P50 inequality values, which seems to confirm the foregoing assumption.

If the focus is on the highest net-market inequality, then after the UK and the southern parts of Italy, regions in Spain (for 1995) and eastern Germany complete the picture. For example, the NUTS 1 region *Isole (IT)* has an M-Gini that is comparable to the (DPI) Gini coefficient of Mexico (0.49)[17]. Interestingly, nearly the same can be said of London.

The regions with the lowest net-market inequality are geographically rather disperse. Along with the Nordic countries, western regions of Germany show markedly low inequality values. Another surprise here is that the list of the top 5 regions with the lowest M-Gini coefficients is completed by *Attiki* in Greece.

[17] source: LIS

Another noteworthy fact is that the highest observed level of disposable income inequality, i.e., *Greater London* in 2000 with a Gini of 0.388, is lower than the lowest net-market inequality value of 0.4 in *Baden-Wuerttemberg*.

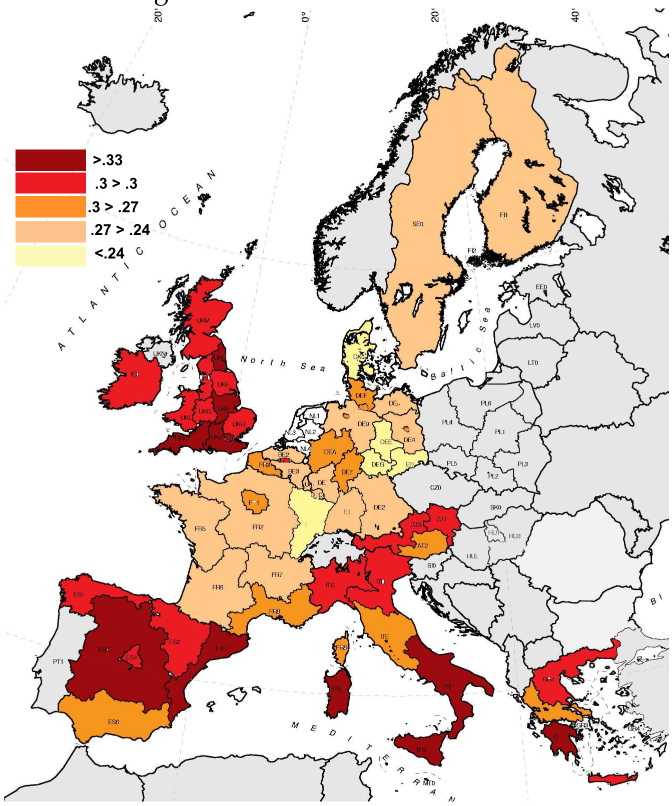
Table 2.8: Highest and Lowest Inequality Levels

1995: M-Gini				**2000: M - Gini**			
Bottom 5		Top 5		Bottom 5		Top 5	
Schleswig-Holstein	0.396	Sur (ES)	0.531	Denmark	0.413	Isole (IT)	0.549
Baden-Wuerttemberg	0.390	Noroeste	0.531	Comunidad de Madrid	0.410	Méditerranée	0.546
Luxembourg	0.389	North & Cumbria	0.529	Attiki	0.410	North & Cumbria	0.534
Brussel	0.385	Wales	0.528	Austria West	0.407	Greater London	0.526
Finland	0.368	Greater London	0.523	Baden-Wuerttemberg	0.406	Sachsen-Anhalt	0.521
1995: Gini				**2000: Gini**			
Bottom 5		Top 5		Bottom 5		Top 5	
Finland	0.217	North & Cumbria	0.364	Est	0.226	North & Cumbria	0.357
Denmark	0.218	Greater London	0.345	Denmark	0.225	Greater London	0.388
Sweden	0.221	Isole (IT)	0.355	Sachsen-Anhalt	0.225	South East exc London	0.342
Thüringen	0.201	Sur (ES)	0.346	Thüringen	0.216	Sud (IT)	0.358
Sachsen	0.204	Voreia Ellada	0.363	Sachsen	0.218	Isole (IT)	0.386

Inequality Levels: Overview 2000

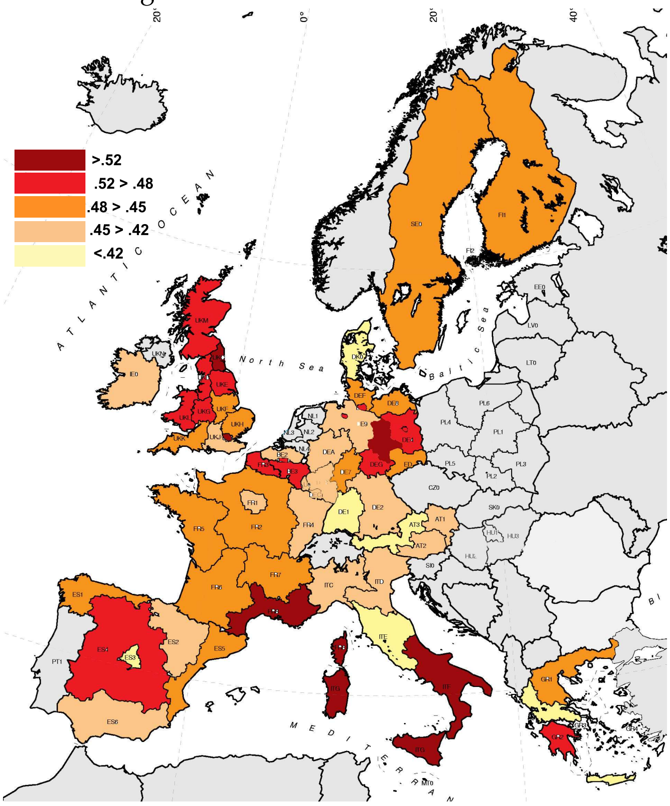
To complete the more anecdotal evidence of the top and bottom inequality values figures, (2.2 and 2.3) display in a regional map of Europe the inequality levels in 2000 for disposable and net-market income measured by the Gini. Even though the actual numbers cannot be fully identified, maps are a useful tool to present the spatial pattern of inequality:

Figure 2.2: Gini: Level in Year 2000



Disposable income inequality (figure 2.2) follows a well-known country pattern. The highest inequality levels are found around the Mediterranean Sea, especially in Italy (Mezzogiorno), Spain (Catalania and Noroeste) and Greece (Attiki), and in the UK (London). Furthermore, higher inequality compared to neighboring regions is found in urban regions such as Brussels, Paris, Bremen or eastern Austria. Relatively low income inequality occurs in eastern and southern Germany, the Nordic countries and most French regions. Dispos-

Figure 2.3: M-Gini Level in Year 2000



able income inequality is in a similar range for a large part of France, Belgium and Germany. Note, however, that Germany is less homogeneous than France (even without eastern Germany).

Comparing the results for disposable with the pattern of net-market income inequality (in figure 2.3), a similar pattern emerges, even though the intra-country variation is higher in most countries - especially in the EU-4 (the UK, Italy, Germany and France).

The UK, Spain and Italy - all countries with less generous welfare states - show high levels of inequality for net-market and for disposable income in most regions. Remarkable differences between the two inequality measures are found in eastern Germany, southern England and in Austria. Eastern Germany was already mentioned above as an example for high unemployment and low upper income inequality, which explains the observed data. On the other hand southern England and the Austrian regions show a relative low degree of net-market inequality but end up with relatively high disposable income inequality. Those regions are characterized by low unemployment rates and (at least in case of the UK regions) higher upper income inequality.

Inequality Trends: Overview 1995 - 2000

Figures 2.4 and 2.5 illustrate the absolute change in inequality values for the 1995-2000 time period.

Overall, disposable income inequality (figure 2.4) was stable or declined in large parts of Europe during the period in question. The only substantial increases occurred in Finland, Sweden, Belgian regions, Hamburg and Isole (IT). The strongest decrease occurred in the regions of *Sur* (Spain), southern Austria and *Est* (France).

The analysis of net-market income (figure 2.5), however, shows some dramatic differences. Inequality increased in most parts of Germany, in the southern parts of Italy and of France and in Finland. And it comes as a surprise that inequality declined in Sweden, given the increase of DPI inequality. In addition to Sweden, inequality declined in most Spanish regions, in the UK, Austria and parts of France.

Even though disposable income inequality remained more or less constant (on average) from 1995 to 2000, the exercise illustrates substantial regional heterogeneity within countries. More importantly, the exercise revealed that net-market inequality developed more heterogeneously during this time period.

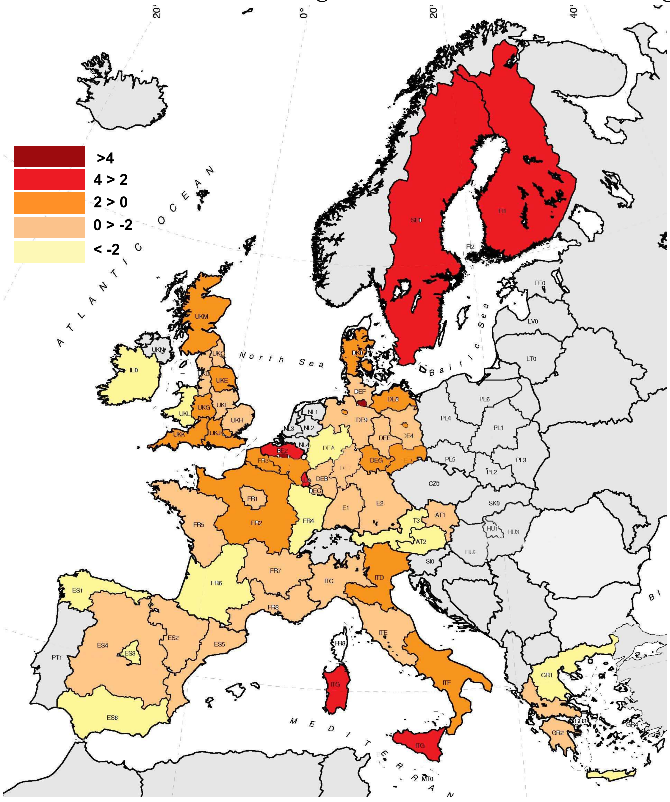
Inequality Trends: EU-4 1985 - 2000

The preceding analysis focused on the 1995 - 2000 period; the following documents the way in which intra-regional inequality has developed since 1985. The analysis is restricted to the EU-4 countries[18] as data are not available for all countries respective of regions.

Country box plots are applied as a presentational tool, thus allowing the as-

[18] The numbers for Belgium and the other country NUTS 1 regions that are available from 1985 can be taken from the data tables in the appendix

Figure 2.4: Gini 1995 - 2000: The Legend indicates absolute Changes x 100



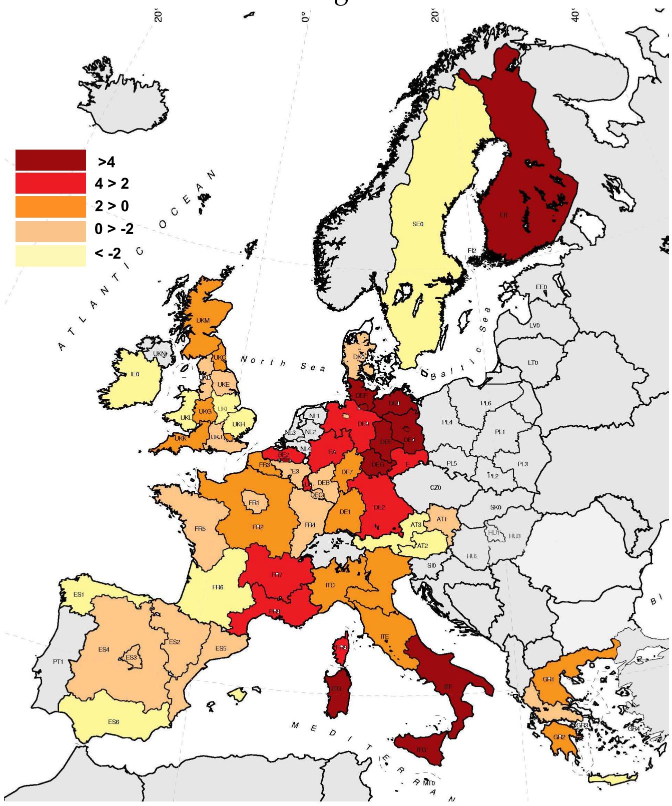
sessment of how strongly intra-regional inequality varies within the respective countries.

Figure 2.6 displays box plots of intra-regional disposable income inequality (Gini) by country since 1985. Figure 2.7 shows box plots for M-Gini.

This exercise permits an analysis of the intra-country differences in inequality as they have changed over time and gives some insights into how redistribution shaped the income distribution in Europe. First, note that, as already previously, the United Kingdom has higher inequality levels in disposable and net-market income than France and Italy. Second, and more insightful, is the development in the four countries over time that reveals interesting differences between disposable and net-market income.

- Figure 2.6 shows that disposable income inequality declined in France over the observed period, while the regional variation increased moderately. Such an increase in the variation between regions is also observed

Figure 2.5: M-Gini 1995 - 2000: The Legend indicates absolute Changes x 100



for Germany[19] and Italy, whereas for the UK, inequality increased further, while the spread between the regions even declined slightly.

- If, instead, M-Gini coefficients are analyzed (figure 2.7), the picture becomes substantially different. Inequality and the spread between regions increased in all four countries. For France, this is especially striking, as the welfare state disguised a slight increase in inequality.

Furthermore, note that in all countries, the between-regional variation is higher for net-market than for disposable income inequality. Hence, transfers reduce differences between regions within the same countries.

The two main observations are as follows: first, redistribution, measured by the difference of DPI and M-Gini, became more important in shaping the income distribution between 1985 and 2000 (with the exception of the UK) and

[19] western Germany

Figure 2.6: Gini: 1985 to 2000

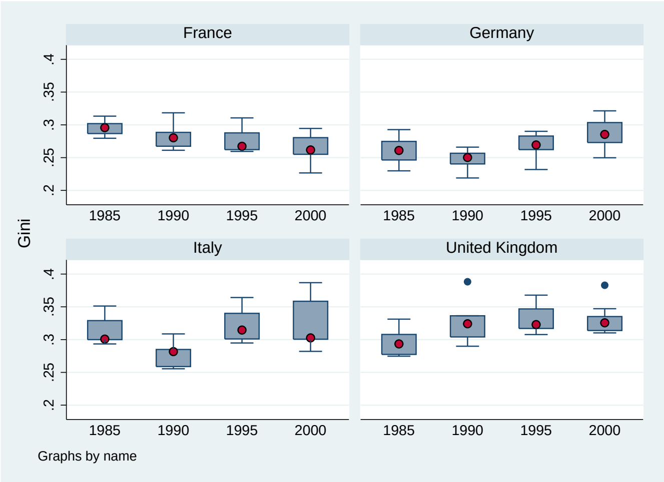
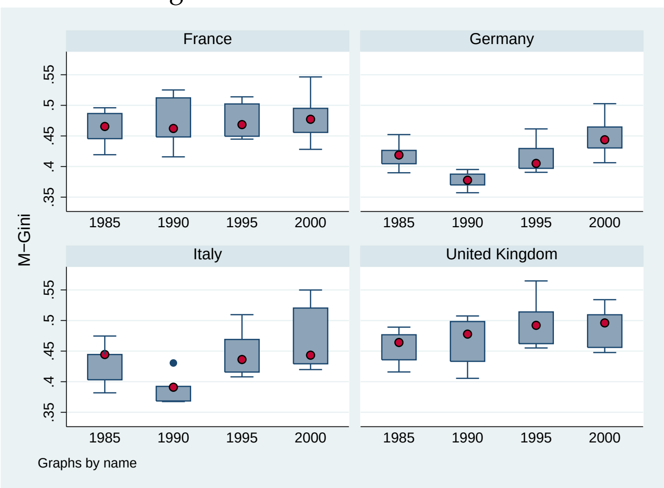


Figure 2.7: M-Gini: 1985 to 2000



second, the regional variation within countries increased over time, especially if net-market income is analyzed.

2.4.3 Summary

The two most important insights of the data evaluation, then, are the following:

- The data emphasize the importance of looking beyond country borders. There exists substantial regional variation in inequality levels as well as trends within countries that average out in country-level analysis.

- The distinction between disposable and net-market income inequality allows one to document the way in which transfer payments shaped the pattern of intra-regional inequality in Europe. Not only does the pattern of net-market inequality levels look substantially different from the general perception but there are substantial changes in inequality that were smoothed out by transfers.

As a caveat, it is important to keep in mind that the quality of the regional data are not very good in every case, so some caution in the interpretation of the results is advisable.

2.5 Extension: Inter-regional Inequality

Up to this point, this chapter has described the intra-regional inequality in Europe from 1985 to 2000. This extension completes the picture by documenting the contribution of inter-regional inequality to overall inequality.

The MLD can be additively decomposed into within and between inequality components. The calculation of the respective regional income shares to calculate the between-regional inequality components is based on regional household mean incomes in year 2000 purchasing power standard units.
Table 2.9 summarizes the MLD components for the full (Panel A) and the EU-4 (Panel B) sub-sample and for net-market and disposable income.

Table 2.9: MLD - Decomposition into Within and Between Components

	Panel A: MLD Decomposition for the Full-Sample							
	Disposable Income				**Net-Market Income**			
	1985	1990	1995	2000	1985	1990	1995	2000
Within	0.183	0.150	0.170	0.157	0.770	0.681	0.757	0.787
Between	0.009	0.013	0.015	0.015	0.015	0.016	0.022	0.025
Total	**0.19**	**0.165**	**0.185**	**0.172**	**0.785**	**0.697**	**0.779**	**0.812**

	Panel B: MLD Decomposition for the EU-4 Subsample							
	Disposable Income				**Net-Market Income**			
	1985	1990	1995	2000	1985	1990	1995	2000
Within	0.190	0.160	0.174	0.165	0.78	0.71	0.76	0.80
Between	0.009	0.010	0.012	0.013	0.014	0.018	0.018	0.026
Total	**0.198**	**0.170**	**0.186**	**0.179**	**0.79**	**0.72**	**0.78**	**0.83**

The contribution of the between components to overall inequality is limited. Inter-regional inequality adds marginally between five (1985) and nine (2000) percent to overall disposable income inequality and around two to three percent to net-market inequality. The contributions of between components to overall net-market inequality are lower because transfers have a relatively stronger impact on intra-regional than on inter-regional inequality.

But the main observation is that between-regional inequality was rising over time; the MLD between components increased between 44 and 87 percent from their 1985 levels to 2000.

2.6 Extension: Median and GDP-Growth

Introduction

The growth of the median income is an indicator that receives considerable attention as a proxy for the well-being of the overall population. Furthermore, the median is applied frequently for the construction of various poverty measures. This extension aims to briefly document the growth of median income across European regions and compare the development to GDP growth.
In a first step, the growth of median income across regions is described. Then, the growing growth-gap between median income and GDP per capita is documented and decomposed into its subcomponents.

Table 2.10 shows the average median growth rates per anno - unweighted and population weighted - over five year periods from 1985 to 2000. Median income grew strongly from 1985 to 1990 and again, but somewhat weaker, from 1995 to 2000. In the period from 1990 to 1995, average regional median income was stagnant or even declining. Note that the full sample, which includes strong growth countries such as Spain, was growing more strongly than the EU-4 sample from 1995 to 2000.

Table 2.10: Average Growth Rates p.a. of Disposable Median Income

		Time Period		
	Sample	85-90	90-95	95-00
Median Growth p.a.	EU-4	2.98%	0.23%	1.45%
Median Growth p.a. (pop. weighted)	EU-4	2.98%	-0.01%	1.34%
Median Growth p.a. (pop. weighted)	Full			2.53%

Table 2.11 displays the growth differential between median income and GDP per capita.
The analysis shows that in the 1985 - 1990 period, the growth rates between median and GDP per capita were similar. In the following period, from 1990 to 2000, GDP per capita was growing significantly faster than median household income. This growth gap is even more pronounced if the median is based instead on net-market income.

Table 2.11: Growth Difference between GDP per Capita and Median Household Income.

Panel A: GDP p.c. - DPI-Median

	Sample	85-90	90-95	95-00
Growth diff. p.a.	EU-4	0.09%	0.53%	0.65%
Growth diff. p.a. (pop. weighted)	EU-4	-0.01%	0.87%	0.90%
Growth diff. p.a. (pop. weighted)	Full			0.66%

Panel B: GDP p.c. - MI-net-Median

	Sample	85-90	90-95	95-00
Growth diff. p.a.	EU-4	-0.32%	1.44%	0.78%
Growth diff. p.a. (pop. weighted)	EU-4	-0.40%	1.74%	1.24%
Growth diff. p.a. (pop. weighted)	Full			0.81%

Preliminary Analysis

How can the growth gap be interpreted? Methodologically, there is no GDP equivalent to *median* household income. However, GDP or more precisely net (after subtracting depreciation) gross national product (GNP) - respectively, gross national income (GNI) - can be converted into *household disposable income* (HDI). HDI is (after dividing by the number of households) roughly comparable to *survey mean* household income. Therefore, it is possible to decompose the growth rate difference into three parts by doing some accounting: (i) into a growth gap between GDP and HDI, (ii) into a growth gap between HDI and mean survey income and (iii) into a growth gap between median and mean survey income.
The main methodical differences are as follows.

(i) The main difference between GDP and HDI consists of capital depreciation, undistributed profits that flow to households in the form of capital gains (only dividends flow into household income), direct and indirect taxes (including social contributions), net transfers and differences of the price deflators for households and GDP.

(ii) HDI and mean survey income are roughly comparable, even though neither top incomes nor imputed rents are captured as income in surveys.

(iii) The difference between median and mean survey income is an indicator of inequality, but note that neither includes top incomes.

Table 2.12 shows the available growth rates for mean, median, HDI and GDP. Unfortunately, Eurostat does not provide reliable HDI income values for all years and regions, and therefore, the difference between HDI and survey mean cannot be distinguished from differences between GDP and survey mean for all time periods. Nevertheless, several conclusions can be drawn from this

Table 2.12: Mean, Median, GDP and HDI Growth Rates p.a. for the EU-4 (population weighted).

	Sample	1985-1990	1990-1995	1995-2000
Mean Growth: DPI	(EU-4)	3.06%	0.43%	1.63%
Median Growth: DPI	(EU-4)	2.96%	-0.01%	1.34%
Mean Growth: MI-net	(EU-4)	3.46%	-0.29%	1.33%
Median Growth: MI-net	(EU-4)	3.35%	-0.87%	1.00%
GDP Growth	(EU-4)	2.93%	0.86%	2.21%
HDI Growth	(EU-4)			1.33%

data. The period 1985 - 1990 was distinctly different from the later periods. GDP, median and mean income (based on surveys) showed similar growth rates. Furthermore, net-market income was growing faster than disposable income.

In the subsequent time periods, the picture changed dramatically. On the one hand, GDP was growing substantially faster than mean and median income, and on the other hand, transfers contributed substantially to the growth of household incomes.

In the last period, the available HDI data allow for a preliminary explanation. Because HDI was growing at the same pace as survey-based household income (even slightly slower), the growth difference between GDP and median does not seem to be driven by top incomes. Instead, along with capital depreciation, undistributed corporate profits are increasing the growth gap between GDP and median income, hand in hand with a growing gap between household median and mean income.

In summary, this analysis demonstrates the following.

- A growth gap between GDP and median income emerged in the early 1990s and did not reverse up to the end of the century.
- This growth differential was, along with capital depreciation, presumably driven by rising (undistributed) corporate profits rather than by an increase of top-incomes.
- Median income was growing more slowly than the comparable survey mean income. This points to an increasing disparity between bottom and upper incomes.
- Transfer payments were a significant source of income growth for the median household.

Chapter 3

Regional Globalization Indicators

"The European Union is without doubt one of the greatest example of the spread of free trade in the world today, and to an economist, that is what globalization is all about." Feenstra [7]

3.1 Introduction

3.1.1 Goal of the Chapter

There are no data on levels and trends of globalization intensities for NUTS-1 regions in Western Europe. This lack of information poses a severe obstacle to the analysis of the impact of globalization at the regional level. The following chapter tries to resolve this deficit. Regional trade and offshoring intensities are approximated using top-down calculations for single industry categories. By linking economic globalization to manufacturing employment, it is possible to distinguish differing globalization intensities within countries. The more heterogeneous a country is in terms of the spatial distribution of its manufacturing sector, the more heterogeneous will be the impact of globalization. Levels and trends of four distinct globalization indicators are documented for the period

1985 - 2000.

3.1.2 Trade and Globalization

There is no unambiguous definition of the term globalization. As Dreher et al. [40] formulate it: *"Depending on the researcher or commentator, it can mean, among other things, the growing integration of markets and nation-states, receding geographical constraints on social and cultural arrangements, the increased dissemination of ideas and technologies, the threat to national sovereignty by trans-national actors; or the transformation of the economic, political and cultural foundations of societies."* From an economic perspective, globalization refers to the increased integration of the world economy. Increasing trade flows, especially through intermediate good trade, capital flows, technology transfers (especially through FDI) and migration are at the core of the story.

The time from the mid-80s to the end of the twentieth century was a period of massive economic integration and increasing openness. The general condition for free trade improved dramatically in many parts of the world as the successful conclusion of the Uruguay Round in 1994 let trade barriers for many products fall worldwide. Even more important, the economic integration of the European Union or, more precisely, the Single European Market was one of the biggest free trade experiments ever implemented. Beyond those political dimensions, trade got a further boost through technological advance, especially through computer and communication technology (ICT) that increased the tradability of goods and services, reduced transport costs and allowed the relocation of production[1]. The explosive increase of trade in intermediates - which received a lot of academic attention in recent years - was a direct consequence of these developments.

As already discussed in the introduction, globalization is - in addition to the financial and technological aspects - mostly about trade in goods (trade in services is a rather recent phenomenon) and, therefore, is intrinsically linked to manufacturing industries. The exposure and the impact of globalization on any geographical unit therefore depend on the size and structure of its manu-

[1] There are several terms to describe the various aspects of this phenomenon - offshoring, outsourcing, vertical specialization, delocalization and international subcontracting.

facturing sector. The first order impact of globalization will be felt primarily in the manufacturing sector.
The manufacturing sector (or the tradable good sector) is accounting in many countries for only a relatively small and declining share of GDP, but if one takes into account that manufacturing production in many countries is regionally concentrated, its importance should not be underestimated. As documented by OECD [41], the economic development of many European regional economies is closely linked to the performance of a few key manufacturing industries. The regional size of the manufacturing sector and the respective composition of industries are the result of various factors that are beyond the scope of this study to discuss. That said, exogenous factors such as spatial effects (trade access) or the availability of resources surely have an important role in the determination of manufacturing patterns.

To clarify terminology: As mentioned above, a very narrow definition of the term globalization is used in this dissertation. While focusing solely on the increasing integration of the world economy perhaps unjustly removes the term "globalization" from its cultural, political and financial aspects, the expression provides a convenient synonym here for economic openness.

The remaining part of this chapter is structured as follows.

- After a short discussion of popular trade measures, the available country-specific evidence on globalization intensity and on the development of manufacturing employment is documented.

- The next section describes the systematic approach to calculating regional globalization indicators and applies the method to regionalize the four openness measures of interest.

- The regional measures are documented extensively in section 3.4.

- To complement the analysis of regional globalization, the final section (3.5) of this chapter describes the construction of regional ICT intensities in manufacturing.

3.1.3 Trade Dependency Indicators

A rough distinction can be made between two groups of trade or economic globalization indicators. The first group reflects the overall volume of trade for the national economies. The second group of indicators tries to capture the role of multinational enterprises. These measures include trade in intermediate products, intra-firm or intra-industry trade. The OECD handbook on globalization [42] gives a comprehensive review of a broad set of possible measures.

The first group includes many frequently used measures of openness. The most prominent examples are the ratio of the average of exports and imports to gross domestic product (GDP) or the share of exports to GDP.
Strictly speaking, these are not measures of openness but indicators of the dependency (or economic integration) of the national economy on the world economy - two countries can have the same trade ratio to GDP but differ in their level of restrictions and tariffs.

The second group of globalization indicators, trade in intermediate goods or intra-industry trade, has received intense attention due to its growing importance and share of total trade. See Hummels [43] for a documentation of the rise of the importance of vertical specialization in global trade. Particularly, the offshoring of business activities (including services) has recently been given much attention, not least because of the supposed adverse effects on domestic employment.
A measure that has been widely used in empirical work is the *outsourcing* indicator suggested by Feenstra and Hanson [8] calculated as the share of imported intermediate inputs in the total purchase of non-energy materials of individual industries. The information in input-output tables (IOT) and more specifically, the information in the imported transactions matrix has been used for this purpose.
The broad application of this measure has become easier due to the increased availability of input-output tables. The findings are very heterogeneous across countries. The offshoring intensities found lie between 8% in Japan and nearly 80% in Singapore. The results for the European countries are between 20% for France and more than 70% in Ireland (based on the year 2000), as documented in OECD [44].

Note that in several studies, there were also less specific measures constructed[2] to give weight to the multidimensional aspects of globalization (Anderson [45], Heshmati [46], Dreher [47]).

Based on these considerations, I construct four single dimensional measures of trade globalization that cover different aspects of economic integration. Those four indicators have a rather straightforward interpretation that is an advantage over other multivariate measures of globalization.

- The first two indicators are traditional trade-based openness measures, i.e., the share of export to manufacturing value-added and share of imports to domestic supply. This distinction between export and import shares may be useful for doing inference, as export-growth benefits the corresponding industry, while import growth is often associated with rising competition for domestic producers.
  Furthermore, note that I set trade in relation to industry value-added and not to gross domestic product (GDP). It is more accurate to compare manufacturing trade to manufacturing value-added instead to GDP. Otherwise, structural change and change in trade intensities could not be disentangled because the output share of service increases in the economies of all industrial countries. Obviously, the indicator has subsequently been interpreted as the degree of dependence on foreign markets or the degree of import competition for the manufacturing sector instead of for the whole economy.

- As a third measure, an indicator for import-competing industries is constructed based on Kletzer [14] by considering changes in the import share (or import penetration ratio). By analyzing the displacement statistics of import-competing industries, Kletzer found that import-related job loss comprises a sizeable share of US manufacturing job loss[3].

- As a fourth indicator, offshoring intensities are constructed based on IOT-analysis of manufacturing industries. The measure is given as the share

[2]The indicators are constructed by combining several measures using principal component analysis.

[3]More Specifically, he finds that the displaced workers are older, less formally educated, and longer tenured than are displaced non-manufacturing workers.

of imported intermediate inputs relative to total intermediate inputs, as outlined in Feenstra and Hanson [8].

3.1.4 Some Facts about Globalization in Europe

To set the stage for the construction of regional globalization indicators, I show some facts about the two components used in their construction - manufacturing employment and trade flows (indicators of the economic integration of countries into the world economy).

Let me begin with a review of the European manufacturing sector. It is well known that the manufacturing sector has been declining in most parts of Western Europe over the last decades. Country-level employment figures, summarized in table 3.1, confirm this without doubt. As shown in the first three columns, the number of people employed in manufacturing declined in all of the countries shown (except Italy and Denmark) during the period from 1985 to 2000. In addition, the last two columns of table 3.1 display regional NUTS-1 minimum and maximum manufacturing employment shares for each country. These numbers highlight the considerable regional variation within larger countries.

It is generally assumed that job losses in manufacturing are mainly a result of productivity gains and restructuring rather than of processes associated more directly with globalization, e.g., the relocation of production (OECD [41], Kirkegaard [1]). However, while the reduction in employment was accompanied by a productivity increase, the share of industry value added to GDP declined nonetheless.

With regard to globalization, there are various sources of openness indicators. In table 3.2, data from the Penn World Table (PWT)[4] and from the ETH Globalization Index[5] (Dreher [47] are shown to document some trends of economic integration in Europe. For both measures, the level in 1985 and the subsequent 5 year growth rates are presented. With regard to the PWT data, two observations should be made. First, from 1985 to 1990, openness was declining

[4]Total trade (exports plus imports) as a percentage of GDP.

[5]The index uses an average of nine indicators measuring either actual flows or restrictions to trade and capital.

Table 3.1: Manufacturing Employment Shares

		1985	2000	Change	Regional Share Min 2000	Regional Share Max 2000
Germany	de	0.28	0.18	-34%	0.06	0.26
France	fr	0.2	0.14	-32%	0.06	0.18
UK	uk	0.18	0.12	-32%	0.07	0.19
Italy	it	0.23	0.23	-2%	0.09	0.32
Belgium	be	0.22	0.16	-27%	0.12	0.19
Austria	at	0.21	0.17	-17%	0.14	0.21
Spain	es	0.21	0.17	-18%	0.05	0.25
Greece	gr	0.2	0.15	-25%	0.13	0.27
Denmark	dk	0.18	0.18	1%	-	-
Sweden	se	0.21	0.17	-20%	-	-
Finland	fi	0.27	0.19	-29%	-	-
Ireland	ie	0.26	0.21	-17%	-	-
Luxembourg	lu	0.23	0.14	-37%	-	-

Data source: Eurostat Regio Database

in all countries, and second, openness was increasing in all (and increasingly strongly in most) countries from 1995 to 2000. The period in between, 1990 to 1995, was more heterogeneous, as some countries where openness declined in the earlier period recovered and others - e.g., Germany or Belgium - saw the PWT indicator decline slightly further.

In contrast, the ETH-KOF index never declined (except in the case of Greece) and is - unsurprisingly for an aggregated measure - less volatile than trade volumes (PWT) alone. Both indicators show similar rankings in 1985, with Belgium and Ireland at the top and Italy and Spain at the bottom of the distribution.

This brief review confirmed the common knowledge that manufacturing was declining and that openness, i.e., globalization intensity, was increasingly strongly from 1995 to 2000. Furthermore, it showed, on the one hand, that there is substantial intra-country heterogeneity in manufacturing and, on the other hand, that large differences between globalization intensities exist.

Table 3.2: ETH-KOF Globalization and PWT-Openness Indicators

	Level 1985	1985-1990	1990-1995	1995-2000
	KOF Index Growth rates: EU Countries			
Germany	57	7%	4%	24%
France	59	13%	1%	16%
UK	74	1%	2%	9%
Italy	50	13%	17%	18%
Belgium	84	7%	1%	6%
Spain	58	16%	9%	16%
Greece	64	-6%	6%	24%
Denmark	69	8%	13%	9%
Sweden	69	17%	7%	5%
Finland	62	12%	15%	15%
Ireland	84	3%	6%	5%
	PWT-Open. Growth rates: EU Countries			
Germany	51	-4%	-4%	40%
France	47	-7%	1%	27%
UK	57	-10%	13%	2%
Italy	45	-13%	27%	11%
Belgium	140	-2%	-5%	27%
Spain	41	-13%	26%	37%
Greece	46	-1%	-7%	45%
Denmark	76	-8%	2%	22%
Sweden	69	-14%	21%	20%
Finland	57	-17%	38%	18%
Ireland	109	-2%	30%	32%

Data source: ETH-KOF, PWT

3.2 Method and Procedure

3.2.1 Calculation Method

In the following section, the concepts used to construct the regional globalization indicators will be described.
Although there are studies of the impact of globalization on European Regions [41], there are no measures to assess the exposure to globalization directly. Here, the calculation of such indicators is based on a top-down approach.

The calculations begin with country-level trade data differentiated by industry categories following the 'Nomenclature générale des activités économiques dans les Communautés Européennes' (NACE) sectoral classification. There are two possibilities to construct the regional indicators depending on the form of the main input data. This data can be either in the form of (i) trade flows, e.g., imports in millions of Euro, or (ii) trade shares, e.g., exports relative to value added or the ratio of imported intermediates to total intermediate consumption.
In both cases, the key idea is to map the trade flows or the trade shares to the location of industries and correspondingly, to the respective region. Note, however, that this approximation procedure cannot take interregional trade flows into account.
How does the construction work and what are the implications of this regionalization procedure? A description and a comparison of both approaches follows.

Method (1): Trade flow allocation

The trade flows of an industry (j) (which belongs to the manufacturing industries (M)) are allocated to a region (i) and are proportional to the corresponding industry employment (B_j) share of the spatial unit.

$$\mathrm{trade}_i = \sum_{j \in M} trade_j \left(\frac{B_{ij}}{B_j} \right)$$

The regional trade openness (globalization) indicator can be defined as the ratio of trade to industry value added as opposed to industry demand or GDP.

$$Glob(Flow)_i = \frac{\mathrm{trade}_i}{va_i}$$

The lower bound of the measure is given by zero if a region has no industry employment. The upper bound is given by the country's trade level. This indicator is defined such that the globalization value of the country (c) equals the value added, weighted sums of the regional measures.

$$\mathrm{Glob}_c = \frac{trade_c}{va_c} = \frac{\sum_{i \in c} trade_i}{\sum_{i \in c} va_i} = \sum_{i \in c} \frac{va_i}{va_c} \frac{trade_i}{va_i} = \sum_{i \in c} \frac{va_i}{va_c} Glob_i$$

Method (2): Trade share allocation

The second strategy is to allocate country-level globalization measures such as the ratio of imports to industry value added for every manufacturing industry (j) to the respective region. The regional indicators are constructed by weighting the country data with the regional employment shares of the corresponding industries (j):

$$Glob(Share)_i = \sum_{j \in M} \left(\frac{trade_j}{va_j} \right) \left(\frac{B_{ij}}{B_i} \right)$$

The lower bound of the indicator is given by zero. However, under the assumption that in every NUTS 1 region at least one person is working in every industry category (j), the lower bound is the lowest ratio and the upper bound the highest ratio of trade to value added for the manufacturing industries.

Comparison

Both methods suffer from the same limitation in that there are no regional productivities ($prod_{ij}$) on the same digit level of manufacturing industries. The difference between the two measures lies in the different treatment of the missing productivities. By expressing value added (va) as employment multiplied by productivity, this difference becomes visible:

$$Glob(Flow)_i = \sum_{j \in M} \left(\frac{trade_j}{va_i} \right) \left(\frac{B_{ij}}{B_j} \right) = \sum_{j \in M} \left(\frac{trade_j}{prod_i} \right) \left(\frac{B_{ij}}{B_i B_j} \right) \tag{3.1}$$

$$Glob(Share)_i = \sum_{j \in M} \left(\frac{trade_j}{va_j} \right) \left(\frac{B_{ij}}{B_i} \right) = \sum_{j \in M} \left(\frac{trade_j}{prod_j} \right) \left(\frac{B_{ij}}{B_i B_j} \right) \tag{3.2}$$

The flow-allocation method (eq. 3.1) calculates regional trade shares on the basis of the regional average productivities ($prod_i$), while the share-allocation method (eq. 3.2) calculates them on basis of average industry productivities ($prod_j$). The distinction becomes important if productivity is not homogenous across manufacturing industries within the country, i.e., $prod_{zj} \neq prod_{ij}$ for all $z \in I$. This is presumably the case in Italy (north-south), for example, or in Germany (east-west). On the other side, there is also substantial variation of productivity across industries.

In summary, the share approach relies on differences between the regions in terms of their manufacturing structure because the measure depends only on the shares of the particular manufacturing industries relative to each other, while the flow approach depends also upon differences in average regional productivity. One cannot say which of the two measures will be more accurate a priori because the question depends mostly on the application.

3.2.2 A Remark on Interregional Trade

This top-down based regional trade allocation method is based on cross-border flows of goods. The systematic construction of a regional trade matrix is not feasible based on current available data because it would require a full set of regional input-output tables. Neglecting interregional trade relations, however, is also problematic.

Trade flows between the regions of a given country will not be measured, but trade flows into and out of small countries will be. In the standard view, smaller countries are thought to be more open than large countries due to their smaller domestic markets. From a regional perspective, however, their trade values wind up too high relative to large country regions because a part of their cross-border trade should conceptually be counted as being interregional trade.

As a remedy, flows of trade will be restricted here to those entering and leaving Europe. This ensures that there is no direct border contact between regions and their respective trading partners and presumably reduces the distorted measurement of regional trade between large and small countries. An unfortunate side effect of the restriction is that all of the trade flows within the single European market are excluded, and these intra-European flows constitute, of course, one of the main drivers of increasing economic openness in Europe.

3.2.3 Globalization Measures

Export Intensity

As an initial measure, I construct regional export intensities. I define the variable EXPEX as (sectoral) export[6] (exp) intensities weighted by the shares of regional employment in industry j (B_{ij}) relative to total regional manufacturing employment (B_i).

$$\text{EXPEX}_i = \sum_{j \in M} \left(\frac{exp_j}{va_j} \right) \left(\frac{B_{ij}}{B_i} \right) \tag{3.3}$$

The share approach is applied because there is no systematic information on whether firms producing for exports have different productivities than firms producing for the domestic market within the same industry category (j).
This prevents the resulting *export intensities* from merely depending on the average productivity of the region. Otherwise, regions with a low productivity relative to the country average would show higher export intensities than their more productive counterparts given an otherwise identical industry structure. The calculation is based on exports to non-European countries (Ex-EU). Regarding the issue (mentioned in the previous section) of domestic market size, this procedure may also alleviate the problem of re-exports[7].

Remark 1. Note that if country "A" exports intermediate goods to country "B" and imports final goods (that used the original intermediate goods as inputs) from "B", then the exports are double-counted.

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[6] to non-EU countries

[7] Due to re-exports, among other things, Belgian exports of manufacturing goods are more than twice as large as the corresponding value added

Import Penetration Ratio

The regional import penetration ratio does not measure actual trade flows but serves as a proxy for import competition in the region (i). The intuition behind this is simply that a region without car production should not be affected by car imports.
The flow approach seems appropriate here, as low productivity regions accordingly end up with higher import penetration ratios than high productivity regions, given identical employment shares.

The ratio of imports from non-EU countries in region (i) (imp_i) to regional industry demand ($va_i + imp_i$)[8] weighted by the regional share of employment in industry (j) is labeled IMPEX_i.

$$\text{IMPEX}_i = \sum_{j \in M} \left(\frac{imp_j}{(va_i + imp_i)} \right) \left(\frac{B_{ij}}{B_j} \right) \tag{3.4}$$

Note that the regional import penetration ratio can - under certain circumstances - be strongly influenced by a single industry category, e.g., importation of electronic components and goods.

Import Competition

The variable *Import Competition* (IC) is defined as the manufacturing worker share under import competition.

$$\text{IC}_i = \sum_{j \in S} \left(\frac{B_{ij}}{B_i} \right) \tag{3.5}$$

, where S = "selection of industries under import competition". An industry (j) is part of (S) if the ratio of imports (imp_j) to industry demand ($va_j + imp_j$) has been growing by more than 11% in the previous period (see Kletzer [14]). For example, the number of industries in (S) in country (c) in the year 2000 depends on the import growth of the respective industries in (c) between 1995 and 2000.

The main methodological differences from the previous variables are that past trade growth is used to determine the level of import competition, that the

[8] Note that ($va + imp$) does not equal total industry demand because imports from within the EU 25 are not included and industry value is not equivalent to manufacturing value added. That is, va_i does not equal the sum of va_{ij} because it includes mining and construction.

variable is determined not by the actual trade flows, but only by the regional employment structure and that the import competition variable depends on an (arbitrary) cutoff value (11%).

Offshoring Intensity

Offshoring intensity is defined as the ratio of imported intermediate goods (IM_j) to total intermediate goods (IT_j) weighted by the industry (j) structure of the region (i). Thus, the regional indicator is the weighted average share of imported intermediate goods to total intermediate goods in manufacturing industries.

$$\text{OFFSM}_i = \sum_{j \in M} \left(\frac{IM_j}{IT_j} \right) \left(\frac{B_{ij}}{B_i} \right) \tag{3.6}$$

, where B_{ij} is the employment of industry j in region I, and M the number of manufacturing industries. The available data do not allow a separation of offshoring activities into intra- and extra-EU flows. Note that if the industry substitutes its production with imported inputs, this will lead to an underestimation of the degree of offshoring because both the numerator and the denominator of 3.6 will increase by the same amount.

3.3 Data

The sources of the input data are the OECD Structural Analysis (STAN) and OECD bilateral trade database for export and import figures, the OECD Input-Output database for the transaction matrices, the EUROSTAT Regio database for employment figures and EUKLEMS [48] for data on capital and on value added by manufacturing industries.

All input-output tables are from the OECD Input-Output database. For the EU-4 countries, IO-tables are available since 1985[9] and for the remaining countries since 1995 (with the exception of Ireland, for which the IOT is only

[9] Data for Italy 1990 is missing. The transaction matrix was approximated using the 1992 supply-use tables (corrected).

available for the year 2000).

The manufacturing industries are classified according to NACE. I distinguish 14 industry categories listed in table 3.3. The availability of regional employment data does not allow a more detailed classification. The regional

Table 3.3: Classification of Industry Categories

NACE	No.	Description
D	15-37	Manufacturing
da	15-16	Manufacture of food products; beverages and tobacco
db	17-18	Manufacture of textiles and textile products
dc	19	Manufacture of leather and leather products
dd	20	Manufacture of wood and wood products
de	21-22	Manufacture of pulp, paper and paper products; publishing and printing
df	23	Manufacture of coke, refined petroleum products and nuclear fuel
dg	24	Manufacture of chemicals, chemical products and man-made fibers
dh	25	Manufacture of rubber and plastic products
di	26	Manufacture of other non-metallic mineral products
dj	27-28	Manufacture of basic metals and fabricated metal products
dk	29	Manufacture of machinery and equipment n.e.c.
dl	30-33	Manufacture of electrical and optical equipment
dm	34-35	Manufacture of transport equipment
dn	36-37	Manufacturing n.e.c.

manufacturing employment figures were partially incomplete and had to be adjusted accordingly.

The construction of the globalization variables requires regional employment data in a compatible industry classification level and compatibility with the LIS timeframe as well, i.e., for every fifth year beginning in 1985 to 2000. The quality of regional employment data are rather poor. The regional classification follows the NUTS 95 rather than NUTS 03 to ensure comparability with the LIS. Note that several regional employment figures - especially those for the UK - had to be adjusted accordingly.

Given the available data, the lowest feasible industry aggregation level is NACE rev.1 R-17. Data availability is particularly poor for the years 1985 and 1990 and, consequently, precludes the application of the NACE level (2) classification. It is no surprise that data quality as well as availability increases greatly over time. Hence, the following adjustments were mostly made for the 1985 and 1990 employment figures.

Missing data points were interpolated using adjacent years whenever possible. If those data were also not available, the number of employees was approximated by the average countrywide growth rate for the specific industry. This assumes that the respective industries were developing homogenously across regions. As this is not feasible in the case of smaller regions, some adjustments were done on a case by case basis. More specifically, rather than applying countrywide growth rates, growth rates of similar regions in terms of geography and economic development were applied to approximate missing figures. If data were missing for an industry category over several years and for most regions, employment was set to zero. This problem, however, arose only occasionally in the case of the leather industry. Note that the leather industry (NACE dc, 19) is in most IO-tables anyway, included as part of the larger textile industry.

The regional employment data from Eurostat cover only the number of employees rather than the number of full time equivalent employees. To calculate comparable employment shares across Europe, the regional employment data were harmonized with country-level employment figures from the better harmonized EUKLEMS database.

As has been mentioned, the data on ICT and total capital per industry are from EUKLEMS database. As KLEMS does not contain estimates for Greece, the respective ICT capital figures were approximated using regional investment data and ICT-related employment figures.[10]

[10]More precisely, the ICT shares of Spain and Italy in 1995 were taken as a starting point and corrected by the difference in ICT-related employment. The country-level data were extended to the year 2000 using net investment figures by applying the perpetual inventory system under the assumption that the depreciation rate for ICT is around 10 percent higher than for total capital. The regional values were approximated with the regional investment share of NACE sectors (j) and (k), which have the highest ICT capital share of all industry categories.

3.4 Descriptive Evidence

The following section documents the regional globalization indicators. An overview is provided based on summary statistics and the correlation coefficients of the different measures. In the following, the focus is on the regional disparities of the four globalization indicators. Maps of European regions and country box plots are applied as descriptive tools. The maps allow one to compare regions visually across different countries and help to provide an impression of the spatial globalization (intensity) distribution within Europe. The box plots give an overview of the globalization indicators by year and country and allow for quick assessment of common trends and development of within-country variations.
The complete data tables can be found in the appendix.

3.4.1 Overview

Summary Statistics

Table 3.4 shows the mean and standard deviation of the globalization indicators separately by year and sample selection.

Table 3.4: Summary Statistics by Year and Sample Selection

		1985		1990		1995		2000	
Globalization Indicators		EU-4	Full	EU-4	Full	EU-4	Full	EU-4	Full
Offshoring	Mean	0.223	-	0.222	-	0.233	0.259	0.245	0.288
(OFFSM)	St.Dev.	0.044	-	0.050	-	0.025	0.071	0.033	0.090
Export intensity	Mean	0.311	0.322	0.291	0.302	0.383	0.360	0.471	0.456
(EXPEX)	St.Dev.	0.071	0.078	0.040	0.053	0.043	0.102	0.052	0.145
Import penetration ratio	Mean	0.170	0.177	0.167	0.173	0.193	0.182	0.251	0.247
(IMPEX)	St.Dev.	0.051	0.055	0.044	0.046	0.054	0.066	0.051	0.071
Import Competition	Mean	0.569	0.557	0.315	0.316	0.399	0.404	0.592	0.611
(IC)	St.Dev.	0.129	0.143	0.227	0.218	0.227	0.258	0.254	0.223

- Offshoring: Average offshoring intensity declined until 1990 and increased afterward. In the full sample, we have higher averages and higher standard deviations.

- Export intensity: Export intensity average and standard deviation both declined from 1985 to 1990. In the subsequent period (1990-2000), average and standard deviation increased strongly. A comparison between the full and the EU-4 samples shows that the average export intensities are similar but that the full sample has a higher standard deviation. This is not surprising, as countries with openness indicators below the sample average (Greece and Spain) and well above the average (Belgium and Ireland) are added to the EU-4 sample.

- Import penetration ratio: The increase of import penetration began in 1990. For the EU-4, the import indicator increased by around 50% in the period 1990-2000. The full sample average is slightly lower than that of the EU-4, but here again, the standard deviation is higher.

- Import competition: There is a substantial fluctuation of the indicator combined with high standard deviations. The highest average import competition is found in 2000, i.e., around 60% of all manufacturing workers were facing increased import competition. This reflects the strong growth of import shares in the period 1995-2000. There is no systematic difference between the EU-4 and the full sample.

In summary, all indicators increased between 1990 and 2000. Furthermore, the relative standard deviations (the coefficient of variation) are lower in 2000 than in 1985, with the exception of IC.

Correlation Between the Indicators

Even though there are differences with regard to content and methodical procedure between the four variables, there are significant positive correlations between them, with the exception of the import competition variable (IC). Table 3.5 shows the Spearman's rank correlations between the four globalization indicators. There is a significant positive correlation between EXPEX, IMPEX and OFFSM in levels and after a within-transformation (i.e., after subtracting the regional variable mean). The variable import competition (IC) is uncorre-

Table 3.5: Spearman's Rank Correlations, all Years

	OFFSM	EXPEX	IMPEX	IC
	Correlation in levels			
OFFSM	1			
EXPEX	0.604	1		
IMPEX	0.522	0.6984	1	
IC	-0.0977	0.005	0.045	1
	Correlation after within-transformation			
OFFSM	1			
EXPEX	0.501	1		
IMPEX	0.370	0.87	1	
IC	0.191	0.366	0.42	1

lated to the other indicators in levels, but there is a positive correlation to import shares after the within-transformation. Not surprisingly, offshoring (i.e., the intermediate import share) is more strongly correlated to import than to export intensity.

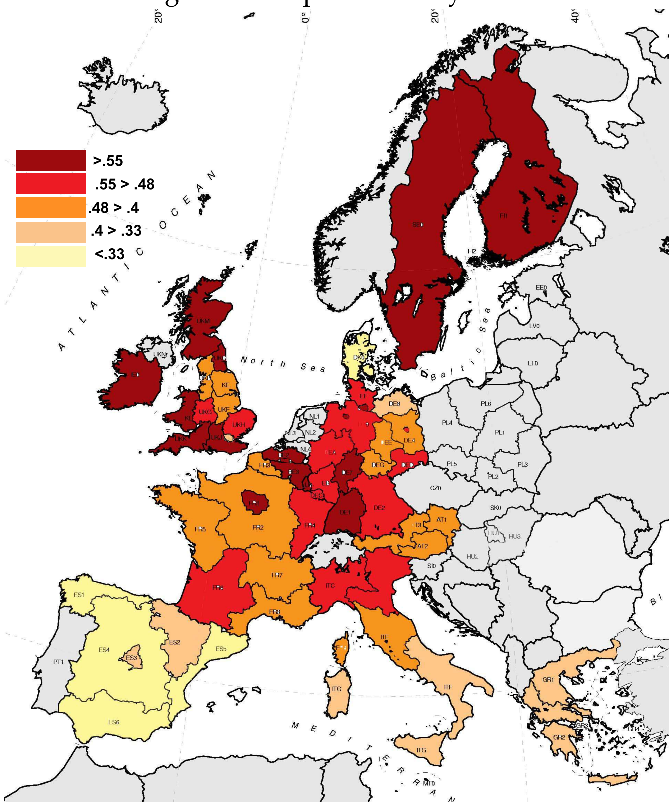
3.4.2 Export Intensity (EXPEX)

Cross-Regional Comparison: 2000

Figure 3.1 gives an overview by indicating the year 2000 EXPEX values on a map of European regions. The very highest levels of manufacturing export shares in 2000 are observed in the Nordic countries, Ireland, regions of Belgium and Bremen. The lowest ratios of export to valued added - around 0.3 - are found in regions of Spain and Greece.

The EU-4 countries - Germany, the United Kingdom, France and Italy - display substantial disparities in their regional export intensities. The export shares within these countries are between 0.4 and 0.6. In Italy, there is a clear north-south pattern, while in Germany, an east-west pattern is visible.

Figure 3.1: Export Intensity: 2000



EU-4: 1985 - 2000

Figure 3.2 summarizes the development of export intensities for the EU-4 countries with box plots for the period 1985 to 2000.

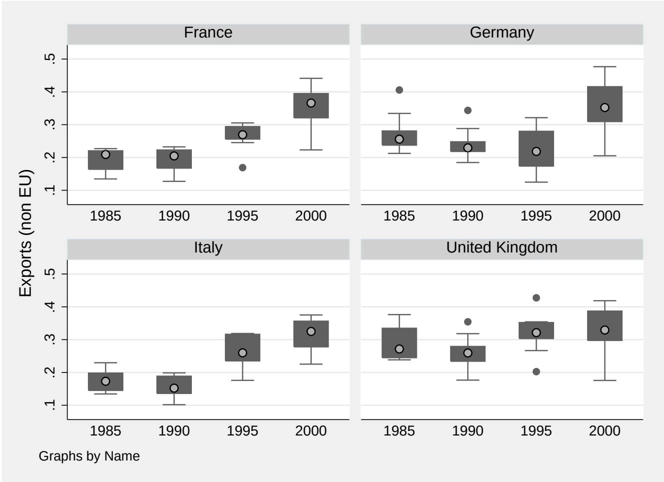
Noteworthy observations include the following.

- There is a marked increase of the export share in all German regions from 1995 to 2000. France and Italy display strong growth since 1990, while not much movement is visible in the UK, even though from higher levels.

- In the period from 1985 to 1990, export shares were stagnant or declining in all four countries.

- The within-country variation was increasing over time, especially in France between 1995 and 2000.

Figure 3.2: Export Intensity 1985 to 2000



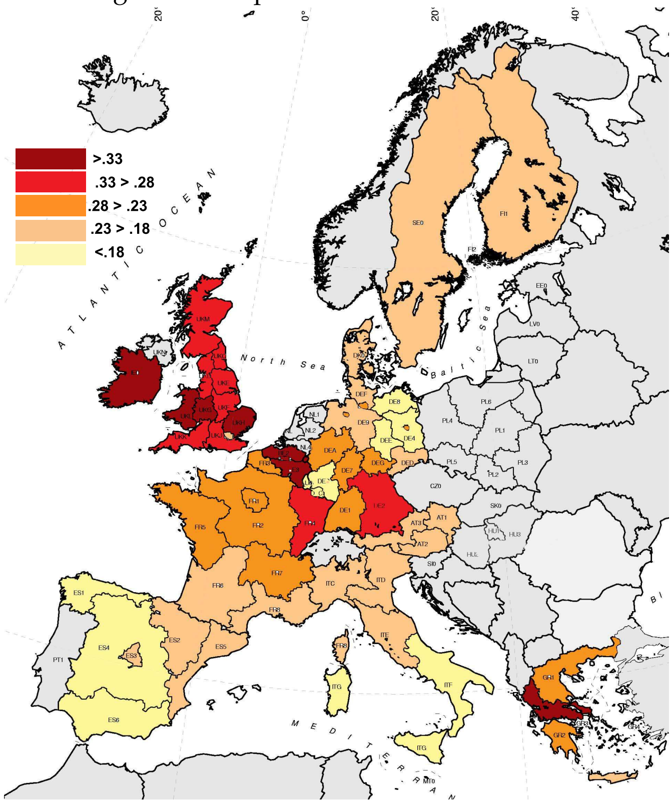
3.4.3 Import Penetration Ratio: IMPEX

Cross-Regional Comparison: 2000

The pattern of the regional import penetration ratios is similar to the one observed for export intensities. Map 3.3 shows the levels of the import indicator for the year 2000. As would be expected from country-level data, the manufacturing import share is highest in Ireland, the UK (especially in the West and East, with the exception of the capital region *Greater London*) and Belgium. The lowest import shares are found in relatively less developed (poorer) regions such as Spain, southern Italy and eastern Germany. Somewhat surprisingly, this group of regions is joined by Luxembourg and Rheinland-Pfalz & Saarland. In Germany and France, the import of electronics has a strong influence on regional import ratios. This explains in part why the regions Bayern and Est (France) show high IMPEX values.

In Greece, the region *Attiki* is the center of the Greek chemical and transport industries and has high import values. Presumably, the region imports substantial amounts of intermediate inputs. Specifically, imports of transport equipment are by far the most important import category (with a share of over 30% of the total).

Figure 3.3: Import Penetration Ratio: 2000



EU-4: 1985 - 2000

The main observations in the figure 3.4 are as follows.

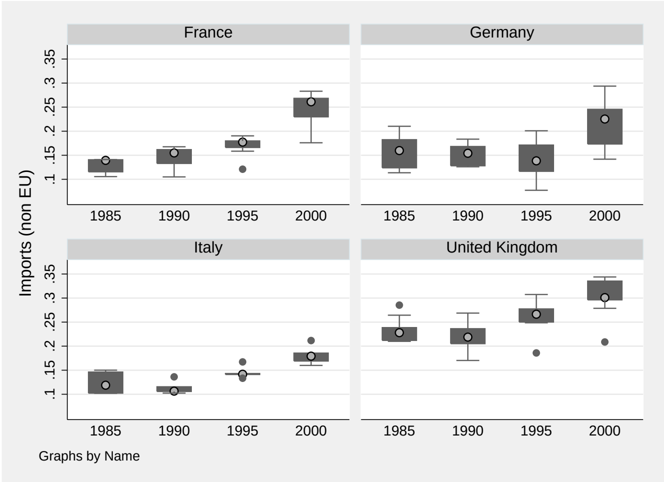
- The overall trends are similar for imports and exports (see figure 3.2). The highest import share, that of the UK, increased even further after 1990.
- Remarkably, the within-country variation is lower in all four countries compared to export intensities, and this characteristic is especially distinct for Italy. This shows that the import penetration ratios across industry categories are more homogeneous than are the export intensities.

3.4.4 Offshoring: OFFSM

Cross-Regional Comparison: 2000

The spatial distribution of offshoring is displayed in figure 3.5. The regional intensities are very heterogeneous, ranking from below 0.2 in France-Ouest up to

Figure 3.4: Import Penetration Ratio 1985 to 2000



0.65 in Ireland. The pattern varies substantially from the picture found for export and import intensities. The highest offshoring intensities are found again in Ireland and Belgium, closely followed by those of Austria and the Nordic countries. Surprisingly, however, Spanish manufacturers are also importing a rather large share of their intermediate inputs in this period. Relatively low values of OFFSM emerge in France, Italy and Greece (again, with the exception of *Attiki*). In Germany, offshoring intensity diverts from the usual east-west pattern, as several Eastern-Länder have relatively high values and Bayern has one of the lowest intensities. In the UK, offshoring intensity is highest in the industrial centers in the south-east and in regions where manufacturing of electronics or cars is relatively important.

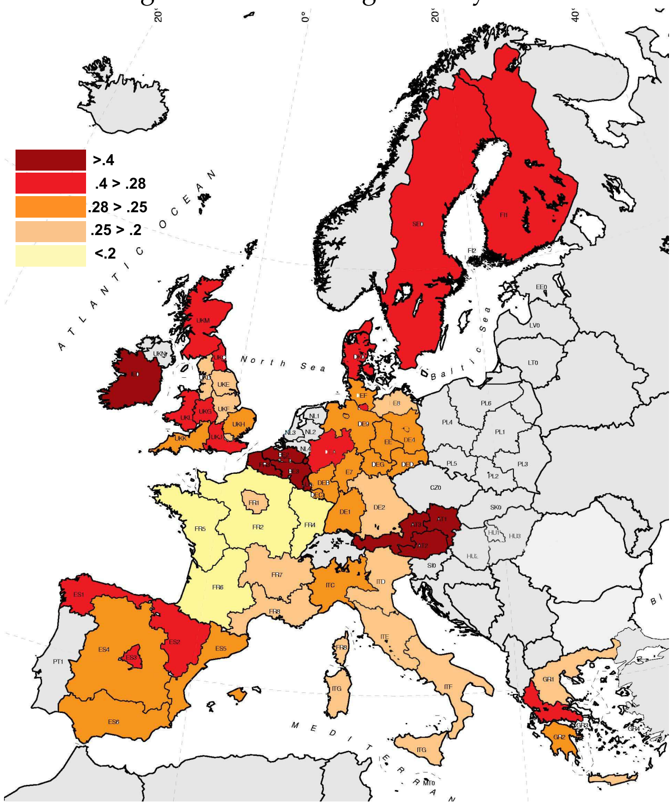
EU-4: 1985-2000

The regional offshoring levels in the EU-4, as displayed in figure 3.6, show strong country ties, but there are substantial disparities within those countries. The differences between the regions with the lowest and highest manufacturing offshoring intensities within the countries are about 15 to 20 percent.

The main observations by country are as follows.

- Germany: Offshoring intensity increased strongly after 1990 from around 0.17 up to 0.27, an increase of more than fifty percent.

Figure 3.5: Offshoring Intensity: 2000

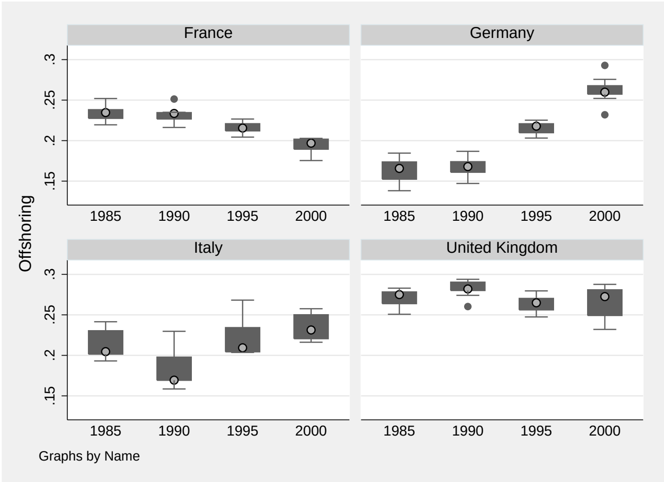


- France: Offshoring intensity declined in France after 1990. Technological change did not stop at the French borders, and production processes in France also became more fragmented. Offshoring was declining in some industries with large regional employment shares, e.g., the production of machinery and motor vehicles.

- UK: The offshoring intensity remained relatively constant over time and was at the highest level of the four countries described here.

- Italy: The period shows a moderate increase in offshoring (with an notable decline in 1990).

Figure 3.6: Offshoring Intensity 1985 to 2000



3.4.5 Import Competition: IC

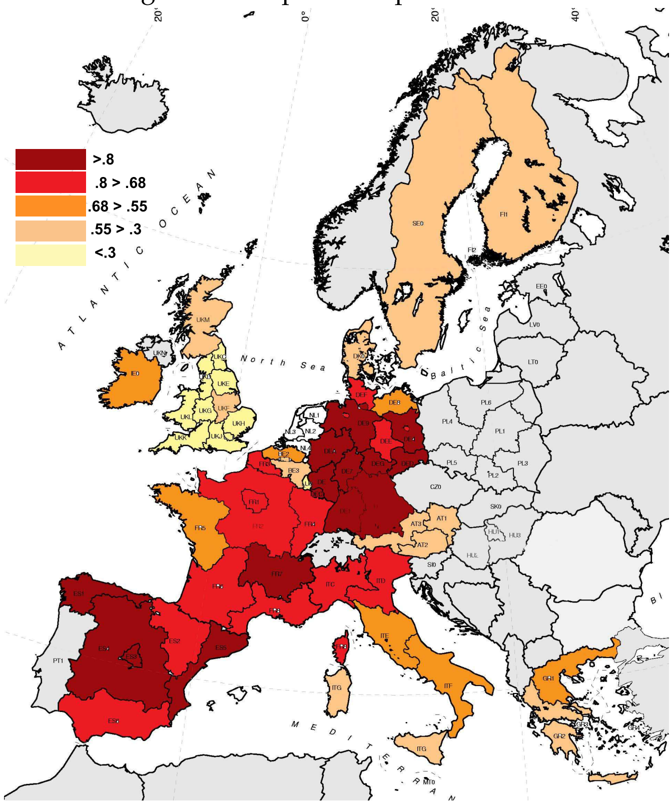
Cross-Regional Comparison: 2000

As can be seen from figure 3.7, in the year 2000, the highest levels of import competition were measured in Germany, Spain, parts of France and in northern Italy. The UK, Austria and the Nordic countries exhibited low import competition because imports did not grow strongly between 1995 and 2000. (Recall that the variable does not take into account the actual or past level of the import share.) The variables show relatively low intra-country variations. This results from the insufficient disaggregation level of regional industrial data. If imports in most (or all) industrial categories increased strongly (i.e., more strongly than the benchmark level of 11%), then there can be no or only very limited intra-country variation.

EU-4 countries: 1985-2000

The box plots in figure 3.8 demonstrate the low intra-country (but high inter-country and high over-time) variation for the EU-4 since 1985. The highest values of import competition by country are for the UK in 1985, for France and Germany in 2000 and for Italy in 1995.

Figure 3.7: Import Competition: 2000



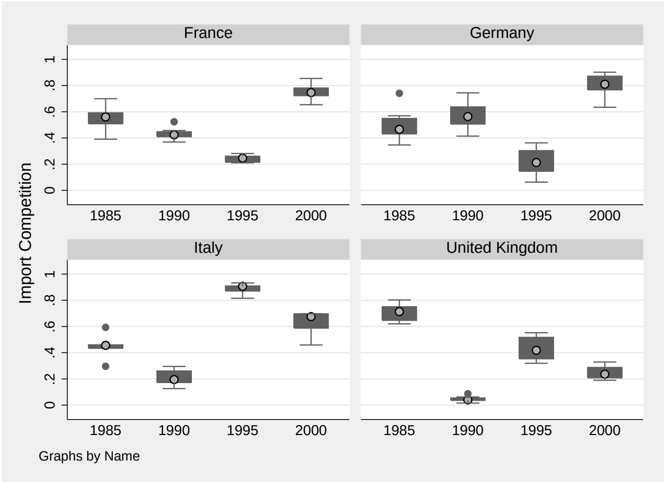
3.5 Information and Communication Technology - ICT

As noted in chapter 1, information and communication technology (ICT) is closely related to globalization and should be part of any econometric specification trying to estimate the impact of globalization. This section briefly describes the construction of regional ICT intensities to complement the preceding openness indicators.

The ICT share in manufacturing is measured as the share of information and communication technology capital relative to total capital. The necessary data for ICT and total capital figures are derived from EUKLEMS, as discussed in the data section.

The procedure to calculate the regional manufacturing ICT levels is identical to the construction of the regional offshoring intensities. The country-level ICT

Figure 3.8: Import Competition 1985 to 2000



shares by industry category are weighted by the respective regional industry employment share. Implicitly, it is assumed that technology is country specific and that regional differences are only due to the composition of the respective industry.

The variable ICT is calculated as:

$$\text{ICT}_i = \frac{cap_j^{ICT}}{cap_j} \frac{B_{ij}}{B_i}$$

, where cap^{ICT} is information and computer technology capital, cap_j is the share of total capital for industry (j), and B_{ij} corresponds to the employment of industry (j) in region (i).

The Variable ICT

Summary statistics of the ICT indicator are given in table 3.6. Average regional

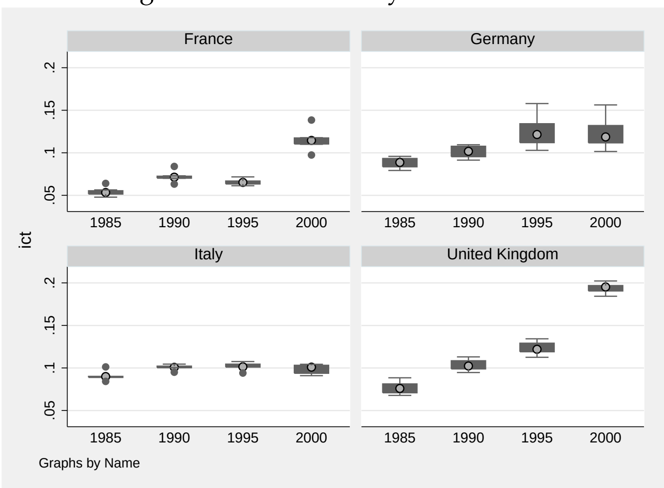
Table 3.6: Summary Statistics by Year and Sample Selection

		1985		1990		1995		2000	
		EU-4	Full	EU-4	Full	EU-4	Full	EU-4	Full
ICT	Mean	0.077	0.080	0.094	0.097	0.107	0.099	0.141	0.122
	St. Dev.	0.014	0.022	0.013	0.019	0.026	0.033	0.038	0.043

manufacturing ICT intensity increased after 1985. Unsurprisingly, growth was strongest in the period from 1995 to 2000. Even within the EU-4 sample, regional standard deviation increased over time. A particularly striking increase occurred between 1990 and 1995.

Standard deviation is higher for ICT than for the globalization indicators. As can be seen by the country box plots in figure 3.9, this is mostly due to higher variation between countries rather than to higher within-country variation, but the difference between the regions (within a given country) with the lowest and highest ICT intensities is around 12 to 40 percent.

Figure 3.9: ICT Intensity 1985 to 2000



- Country trends are important: In particular, Italy and France show only minor intra-country variations.

- There was a very strong ICT increase in the UK after 1985. In Italy, the ICT ratio remained fairly constant. France had very low ICT values in 1985 and remained at that level until 1995. Germany displays a moderate increase over time. The increase in intra-country variation there is largely due to German reunification.

Part III

Econometric Investigation

Chapter 4

Econometric Approach

4.1 Procedure

Both the broad research goals of this study and the possible concerns about the reliability of the input data make a careful and extensive econometric analysis necessary. Meta-analysis techniques are applied as a tool to evaluate the relationship of interest in a most systematic way.
Meta-analysis is a quantitative literature review and aims to identify the causes of different empirical findings on the same subject. The guidelines for building a meta-database and the subsequent use of meta-regressions are drawn from Stanley [49]. As in a traditional meta-analysis of a series of empirical contributions, the most crucial step is the selection of studies and results to be included in the sample. But the main difference to a standard meta-analysis is that all of the necessary input data (the coefficients) are generated by the author, i.e., the data generation process is fully transparent. This has the advantage that the coefficients (the effect size) are fully comparable.
The following section explains this econometric approach and outlines the meta-analysis process.

It is important to note that there is no established empirical model. A review of the studies summarized in table 1.1 shows that, as an expedient, many contributions follow the Kuznets model of structural change (Kuznets [50]) as a guideline to set up their empirical models. This is unsatisfactory in light of the findings that the Kuznets argument is not supported by inequality data (Li et al. [38]), at least not in the developed country context.

However, the econometric procedure requires a regression equation as a starting point. A promising strategy is to build upon the foundation given by the research on wage inequality and job displacements, as both phenomena contribute to changes in income inequality. The literature stresses the role of offshoring as a main characteristic of economic globalization. Furthermore, it emphasizes the importance of technology to explain rising wage inequality, as discussed above. In particular, the role of information and communication technology should not be neglected, as has been done in most studies on income inequality (with the notable exception of Jaumotte et al. [21]), given the inter-linkage of globalization and technological progress.

Based upon the foregoing, a basic regression equation is formulated as follows:

$$\text{INEQ} \;=\; \beta_1\,\text{GLOB} + \beta_2\,\text{TECH} \;+ \rho\,\text{CONTR} \;+\; u \tag{4.1}$$

The important feature of the equation is that two variables separately capture the impact of globalization (GLOB) and the impact of technology (TECH) on inequality (INEQ). The choice of control variables (CONTR) and the specifications of the error term (U) are discussed extensively in the following section 4.2. In short, this equation serves as the starting point and guideline to construct the so-called `meta-database`.

In a first step, many feasible model specifications are determined based on that equation. The specifications contain, in particular, all combinations of (1) alternative dependent (inequality measures) and (2) primary independent (globalization measures) variables, (3) the set of control variables, (4) the estimation methods and (5) the structure of the error term.
In a second step, all the feasible regressions are run, and the findings (i.e., the resulting coefficients) are compiled into the `meta-database`. Note that the results of those primary regressions are not presented in detail.
In a third step, the coefficients in the `meta-database` are evaluated using descriptive statistics and regression methods. The dual goal here is to determine the most robust results and at the same time, to identify possible effects of the

model specifications.
These findings serve also as a basis for the specification of a benchmark model for analyzing the impact of globalization on inequality. Subsequently, this regression is used to address additional robustness concerns and for further estimations.

Overall, the use of a meta-analysis has the convenience of being a very transparent procedure because all regression results (rather than just a selection made by the author) are incorporated into the evaluation. Furthermore, the meta-analysis has the advantage of allowing the efficient comparison of various combinations of dependent and independent variables.
Sala-I-Martin [51] applied a similar strategy by testing which variables were systematically significant in a growth regression framework. In this case, however, the proposed procedure is focused on the econometric specification (in addition to the choice of variables).

Predictions regarding the sign of the coefficients of interest, β_1 and β_2 in eq. 4.1, are ambiguous at this point. Two distinct hypotheses with opposing predictions can be formulated regarding the impact of globalization and technology on the income distribution.

- Globalization and/or information and communication technology are increasing inequality by pushing the relative demand for skilled workers or worsening the labor market outcome for low-skilled workers.

- Inequality is reduced due to positive effects on productivity, which leads to lower unemployment rates, among other things. This second argument is based on empirical results suggesting that globalization (with special regard to offshoring) increased productivity on the single industry level (see Olson [52] for a review).

Ultimately, whether and in what direction income inequality is affected by globalization and technology is a matter to be settled by the data. Perhaps, transfers play an important role in shaping the actual outcome.

4.2 The Meta-Database

4.2.1 Introduction

This section describes the compilation of the meta-database, i.e., the selection process and the specification of the regressions on which the coefficients in the meta-database are based. As already mentioned, the main steps to set up the `meta-database` are as follows.

(i) Based on the basic test equation (4.1), several sets of dependent and independent variables are specified,

(ii) the appropriate test methods are selected based on specification tests

(iii) and all the proposed regressions are run. The actual results of all of these regressions are not displayed, however. Instead, the resulting parameter estimates are compiled into a meta-database of regression coefficients.

4.2.2 Sample Description

The units of analysis are NUTS 1 regions during the time period 1985 to 2000. The database covers thirteen countries[1], of which five are not further subclassified and are therefore counted as one region each in accordance with the definitions of NUTS 1. The overall number of regions (i) is 61 (N).

A distinction is made between an *EU-4* sample, which consists of western Germany, France, United Kingdom and Italy, and a *full* sample, which additionally includes Spain, Greece, Austria, Belgium, Finland, Sweden, Denmark, Luxembourg and eastern Germany. The panel has four time periods (t) in five year intervals because data are not on hand for every year. Data are available from 1985 forward for the *EU-4* sample and since 1995 for the additional regions in the *full*[2] sample. The data form an unbalanced panel.

As a cautionary measure, several regions are removed from the sample because either the data quality of the dependent variables (LIS-based inequality estimates) is very low or they show strong outlier characteristics. The city re-

[1] The Netherlands and Portugal are not included due to missing regional data in the LIS.
[2] The full sample corresponds to the EU-15 without Portugal and the Netherlands.

gions Hamburg and Bremen are dropped due to the first reason, while the Spanish region `Canaries` and `Luxembourg` are removed due to the second.

4.2.3 Specifications

Test Equations

The basic econometric model is based on equation (4.1), i.e.:

$$\text{INEQ}_{it} = \alpha + \beta_1 \text{GLOB}_{it} + \beta_2 \text{TECH}_{it} + \rho\,\text{CONTR}_{it} + u_{it}, \;\; i = 1, ..., N \text{ and } t = 1, ..., T \tag{4.2}$$

where subscript (i) denotes regions and (t) time periods.
The regression 4.2 is run for several dependent inequality variables (INEQ) to reduce the incidence of spurious findings and to distinguish between lower and upper income-sensitive measures.

Specifically, three intra-regional income inequality measures - Gini, MLD and P90P50 - are used. In addition, these are applied in each case on the basis of disposable income as well as net-market income. The goals here are to obtain more precise estimates and to gain insights into the role of redistribution with regard to the impact of globalization.

As main independent variables (GLOB), the four measures (OFFSM, EXPEX, IMPEX and IC), which were discussed in the previous chapter, are applied separately at a time. The variable ICT is included as proxy for technological progress (TECH) in all regressions.

The choice of controls (CONTR) is a nontrivial task, especially in view of the lack of a common workhorse model that fits the research questions. The model (respective of the choice of independent variables) is set up as follows.

(i) The first model is limited to the primary variables with a direct link to the research questions - globalization intensity GLOB, and technology intensity TECH - complemented by the share of industrial production relative to GDP (IND-VA). It is important to control for structural change, given that both GLOB and TECH do not take into account the size and development of the manufacturing sector. These three variables build the *basic* model.

(ii) In a second step, further variables are added to the basic model to control for regional characteristics that influence the outcome.
These control variables can be ordered into two subgroups. The first group includes indicators of the economic development and the economic structure of the region. The second group contains measures of labor market rigidity, social and educational variables.
Economic development is, to some extent, already covered by the share of industry value added relative to GDP. In addition, the share of agricultural employment relative to total employment is added to cover rural regions. Furthermore, an age dependency indicator is included, covering the share of the population older than 65, because the income data were not restricted to the working age population. The *basic* model plus the agricultural (AGR) and the age share (AGE) constitute the *extended* model.

(iii) As a further measure falling in the second category of controls, the application of patents per million inhabitants is included. This variable can be seen as a proxy for the level of high skill education and for the presence of research clusters (see (OECD [41]). Note that the patent variable can be interpreted as an approximation of the technological development of a region, but not for the technological state of its production sector (which is already captured by ICT).
As an approximation of labor market rigidity, the share of unionization[3] is applied even though the variable is not available on the regional level. The inclusion of labor market variables is common to most such studies either in the form of a measure of wage bargaining or a measure of unionization as a percentage of the workforce.
The *extended* model plus the number of patent applications (PAT) and union share (UNION) complete the *full* model.

GDP per capita has not been included in the model, despite the fact that regional growth may have substantial impact on the income distribution. On

[3]As an alternative variable, wage coordination is sometimes applied to measure labor market conditions. I do not include it due to its more limited availability.

one hand, this allows the model to capture the impact of globalization through higher growth rates. On the other hand, if rich or rapidly growing regions are likely to be more open, this generates an omitted variable bias. Hence, the globalization variable may capture unrelated economic development or growth effects on the income distribution. Note, however, that the variables patent application (PAT) and the employment share of agriculture (AGR) are substantially correlated to GDP per capita and therefore mitigate the problem. Nevertheless, the impact of GDP is discussed in a subsequent robustness analysis to further address these concerns.

Overall, the model specification deviates slightly from the econometric studies on household inequality outlined in chapter 1: Many studies, at some point, make a reference to Kuznets [50] and try to control for the inverted U-shape pattern of inequality and economic development as between-sector inequality rises during the transition process. Empirically, this is done by either including GDP and squared GDP in the analysis (Li et al. [38] and Dreher et al. [19]) or by applying sector dualism variables (Alderson and Nielson [15]). As already mentioned, for my approach, however, the Kuznets argument is of secondary importance because it is primarily an issue in developing countries.
Additionally, the model does not incorporate a measure capturing the educational level of the population (e.g., the secondary school enrollment ratio) because first, data availability before 1995 is rather scarce, and second, the measure would be difficult to interpret in a regional analysis due to the relatively high mobility of young people, which weakens the direct link between skill in the workforce and secondary school enrollment.

In summary, the following three sets of control variables are applied:

$$\textit{basic:} \quad \text{CONTR}_{it} = \text{IND-VA}_{it} \tag{4.3}$$

$$\textit{extended:} \quad \text{CONTR}_{it} = \text{IND-VA}_{it} + \text{AGR}_{it} + \text{AGE}_{it} \tag{4.4}$$

$$\textit{full:} \quad \text{CONTR}_{it} = \text{IND-VA}_{it} + \text{AGR}_{it} + \text{AGE}_{it} + \text{PAT}_{it} + \text{UNION}_{it} \tag{4.5}$$

Summary Statistic and Correlations

Table 4.1 documents the mean and standard deviation of the applied variables. At this point, the inequality and globalization measures (including ICT) will not be further discussed, as they were already documented extensively in the preceding chapters. With regard to the remaining variables, a significant positive trend is only visible for the number of patent applications. A decline occurred in the industrial sector, while the share of elderly people, the union share and the employment share of agriculture remained roughly constant over time.

Table 4.1: Sample Summary Statistics

Code	Name	1985 Mean	1985 Standard deviation	1990 Mean	1990 Standard deviation	1995 Mean	1995 Standard deviation	2000 Mean	2000 Standard deviation
GINI	DPI Gini	0.28	*0.03*	0.27	*0.03*	0.29	*0.04*	0.29	*0.03*
M-GINI	MI-net Gini	0.43	*0.04*	0.42	*0.05*	0.45	*0.04*	0.46	*0.03*
MLD	DPI MLD	0.17	*0.05*	0.15	*0.04*	0.16	*0.05*	0.15	*0.04*
M-MLD	MI-net MLD	0.79	*0.15*	0.73	*0.20*	0.79	*0.14*	0.82	*0.13*
P90P50	DPI P90P50	1.81	*0.16*	1.81	*0.19*	1.89	*0.20*	1.89	*0.19*
M-P90P50	MI-net P90P50	2.10	*0.24*	2.13	*0.33*	2.23	*0.29*	2.27	*0.26*
OFFSM	Offshoring	0.22	*0.04*	0.22	*0.04*	0.25	*0.06*	0.28	*0.09*
EXPEX	Export intensity	0.32	*0.07*	0.31	*0.06*	0.36	*0.10*	0.45	*0.14*
IMPEX	Import intensity	0.16	*0.05*	0.16	*0.04*	0.17	*0.06*	0.24	*0.06*
IC	Import Competition	0.55	*0.14*	0.29	*0.21*	0.40	*0.25*	0.59	*0.22*
ICT	Share of ICT capital	0.08	*0.02*	0.09	*0.02*	0.10	*0.03*	0.12	*0.04*
PAT	Patent app. per Mio. inhab. (logs)	3.82	*1.29*	3.36	*1.69*	3.82	*1.35*	4.29	*1.44*
IND-VA	Industry value added to GDP	0.32	*0.07*	0.31	*0.07*	0.26	*0.06*	0.24	*0.06*
AGR	Agricultural employment share	0.06	*0.05*	0.05	*0.04*	0.06	*0.07*	0.05	*0.06*
AGE	Share of population (65+)	0.15	0.02	0.14	0.02	0.14	0.02	0.16	0.01
UNION	Union share x 100	36.5	17.0	33.0	16.6	33.0	16.6	29.0	15.7
MFS[1]	Manufacturing employment share	0.21	0.06	0.18	0.05	0.16	0.06	0.14	0.05
GDPC[1]	GDP per capita (in logs)	9.78	0.22	9.92	0.23	9.85	0.31	9.97	0.31

[1] MFS and GDPC are not part of the meta-database specifications but are applied in a later section.

To identify possible collinearity issues, table 4.2 shows the Spearman's correlation coefficients for the regressors. Overall, the correlations seem to be

Table 4.2: Spearman's Correlation Coefficients

	OFFSM	EXPEX	IMPEX	IC	ICT	PAT	IND-VA	AGR	AGE
OFFSM	1								
EXPEX	0.480	1							
IMPEX	0.555	0.687	1						
IC	-0.09	0.007	0.049	1					
ICT	0.152	0.480	0.464	-0.11	1				
PAT	0.077	0.402	0.287	-0.05	0.395	1			
IND-VA	-0.08	-0.17	-0.07	-0.03	-0.15	0.095	1		
AGR	-0.31	-0.42	-0.53	0.107	-0.53	-0.47	-0.03	1	
AGE	0.022	0.076	0.082	0.253	0.162	0.014	-0.00	0.13	1
UNION	0.387	0.145	0.178	-0.23	0.166	0.071	0.148	-0.12	0.112

unproblematic. The highest correlations are found between the globalization variables (with the exception of IC), which is not surprising given that those measures were constructed based on the same methodical procedures. The calculation of variance inflation factors (VIF) confirms that collinearity is a relatively minor problem. Some experimentation showed that the VIF is sensitive to the variable patents and union share[4].
Note that a panel data unit root test (Kyoung [53]) is clearly rejected for all dependent variables.

Specification of the Error Term

This subsection discusses the structure of the error term u_{it} in equation 4.2.
Most regions[5] are under the scope of institutional and political factors that are determined on the country level. This holds at large for income distribution as well as for the globalization intensity. For example, regional inequality is shaped by the respective country tax regime and the level of import competition by country-specific tariffs. Furthermore, there are unobserved region-

[4]The VIF rises after within-transformation for patents (PAT) and union share from around 1.5 to around 4.5, based on a *full* model specification including offshoring. The variable PAT shows especially high signs of collinearity in wave four.

[5]Except the economically small country-regions Denmark, Finland, Sweden, Luxembourg and Ireland

specific factors - such as geographic peculiarities or cultural traits (Tabellini [54]) - that influence the regional economic structure.

Standard panel estimation techniques handle the presence of such unobserved factors, provided that these factors remain constant over time. That assumption may hold in the case of cultural or geographical traits but does not necessarily do so for country-level factors.
In general, the country-level influence on variables is not problematic per se and constitutes an important part of the results, but unobserved time-variant country effects may bias the results. Furthermore, these distortions will vary strongly between countries because they depend on the respective number of regions. As an example, consider the strong growth dynamics in Spain from 1995 to 2000.

The structure of the error term u_{it} and the appropriate regression methods are determined based upon these considerations. The following compositions of u_{it} are considered:

$$u_{it} = \mu_c + \epsilon_{it} \tag{4.6}$$

$$u_{it} = \mu_c + \gamma_t + \epsilon_{it} \tag{4.7}$$

$$u_{it} = \mu_c + \gamma_t + \gamma_{ct} + \epsilon_{it} \tag{4.8}$$

$$u_{it} = \eta_i + \epsilon_{it} \tag{4.9}$$

$$u_{it} = \eta_i + \gamma_t + \epsilon_{it} \tag{4.10}$$

$$u_{it} = \eta_i + \gamma_{ct} + \epsilon_{it} \tag{4.11}$$

, where μ_c captures country-specific effects, η_i region-specific effects, γ_t is picking up overall time effects, γ_{ct} time-variant country effects, and ϵ_{it} is the i.i.d. error term.

In the first three error specifications (4.6 - 4.8), it is assumed that unobserved effects are present that are country-specific but constant over time. Ordinary least squares regression including country (4.6) and time dummies (4.7) and additional interaction terms between country and time dummies (4.8) will be an efficient estimator under the assumption of no region-specific effects.

This pooled cross-section regression allows for the estimation of regional variables that are constant over time, and it has the advantage that it keeps cross-sectional information. This is a desirable property because household-based inequality measures are not very volatile in the short run, and as a consequence, a large part of the variance is cross sectional and not time variable.

The next error specification, a one-way (4.9) or a two-way (4.10) error component model (depending on the inclusion of time effects γ_t), assumes the presence of unobserved regional effects. One can expect to find evidence for unobserved regional effects on top of unobserved country effects because many possible regional characteristics (such as geographical location or the degree of urbanization) cannot be controlled for in the model. The OLS estimates are biased in the presence of η_i even though presumably, country dummies capture a substantial part of the regional fixed effects.

Experimentation with various specifications showed that a generalized Hausman test for poolability remains inconclusive, i.e., depends on the specification. However, either the standard fixed effect (FEM) or the random effect (REM) model is a valid estimator depending on the correlation of the unobserved error components η_i with the regressors. Applying FEM captures only the within variation of the data but by doing so also reduces the possible of an omitted variable bias. In addition, the random effects model (which keeps some of the between-region variation) is applied as an efficient estimator if $E(X_{it}\eta_i) = 0$. The presence of cross-sectional dependence violates the assumption of FEM and REM models if the unobserved factors that create interdependencies across cross-sections are correlated with the regressors. The standard Breusch-Pagan LM test for cross-sectional dependence is not valid because the dataset has the form of small T and large N. In this case, the parametric testing procedure proposed by Pesaran ([55]) can be applied. The Pesaran test-statistic is accepted at the usual confidence levels, thus indicating that cross-sectional dependence is not an issue in the data-set, given the proposed specifications.

The final specification (4.11) controls for unobserved, time-variable country effects in addition to regional fixed effects. This is important given the varying number of regions per country and the intermixture of regions and countries in the sample.

Specification 4.11 relies also on either FEM or REM models but includes interaction terms (γ_{ct}) of time and country dummies on top of the regional effects[6]. Unfortunately, this leads to a substantive loss of information on globalization and inequality. It remains to be seen whether the elimination of unobserved time-variable country effects outweighs the informational loss.

These specifications can be summarized as follows. Three estimation methods - OLS, FEM, REM - are applied in combination with the respective dummy setting. The error compositions 4.6 and 4.9 are described as no (time) dummy specification (ND), the error terms 4.7 and 4.10 as time dummy specifications (TD) and 4.7 and 4.11 as time-variable country dummy specification (CT).

4.2.4 Summary

The size of the meta-database is documented in table 4.3. The content is as follows.

- Every regression is replicated six times because the analysis is based upon three distinct inequality measures - the Gini, MLD and P90P50 - which are at any one time applied separately for disposable and for net-market income.

- Regarding the right hand side of equation 4.2, the regressions are run for each of the four globalization variables separately. This procedure should reduce potential collinearity issues strongly.

- The three sets of control variables (eq. 4.3, 4.4, 4.5) - *basic*, *extended* and *full* - are applied.

- Based on the error structures given in equations 4.6 to 4.11, three dummy specifications (ND, TD, CT) and three estimation methods (OLS, FEM, REM) are used.

In summary, the database contains coefficients of a total of 1296 regressions or 216 regressions per inequality variable.

[6] To avoid perfect collinearity, time-variable country effects are applied only to countries counting as more than one region!

Table 4.3: The Meta-Database

Category	Number of Regressions
DEPENDENT VARIABLES	6
Gini, MLD, P90P50 for disposable and net-market income	
GLOBALIZATION	4
Offshoring, exports share, import penetration ratio, import competition	
MODEL SPECIFICATION / CONTROLS	3
basic = IND-VA	
extended = *basic* + AGE + AGR	
full = *extended* + PAT + UNION	
METHODS	3
OLS, FEM, REM	
DUMMY SPECIFICATION	3
No (time) dummies (ND)	
Time dummies (TD)	
Time-variable country dummies (CT)	
SAMPLE	2
Full sample / balanced EU-4 sample	
Total number:	1296
Number per dependent variable:	216
Number per globalization variable:	324

As the appropriate model is not known a priori, it is convenient to use a covariance matrix robust to heteroskedasticity in all specifications.

Chapter 5

Evaluation and Results

5.1 Overview

This chapter is subdivided into two parts.

(i) The first and larger part presents the results of the meta-analysis. The meta-analysis aims to evaluate sign, size and significance of the different parameter-estimates and to identify possible specification effects. The results are documented in a two-step procedure.

  (a) In the first step, some descriptive evidence is given for size and significance of the parameter-estimates in the meta-database. As a caveat, note that the mean of the coefficients and p-values has to be regarded with some caution because not all specifications are efficient in every setup. More precisely, there are no systematic in-depth tests done if the choice of the error structure and the respective regression method is appropriate under every model specification.

  (b) In the second step, the analysis is complemented by running meta-regressions where the coefficients and the corresponding p-values are used as dependent variables. In doing so, the goal is to identify possible effects of the influence of inequality measurement, sample size, model and dummy settings.

(ii) In the second part of the chapter a regression model is specified as a benchmark for further estimations based upon the findings of the preceding meta-analysis. Subsequently, this regression is used to analyze the robustness of the results and to discuss the interdependence of structural change and globalization. The importance of growth effects and possible endogeneity concerns about the globalization variables are addressed.

5.2 Results of the Meta-Analysis

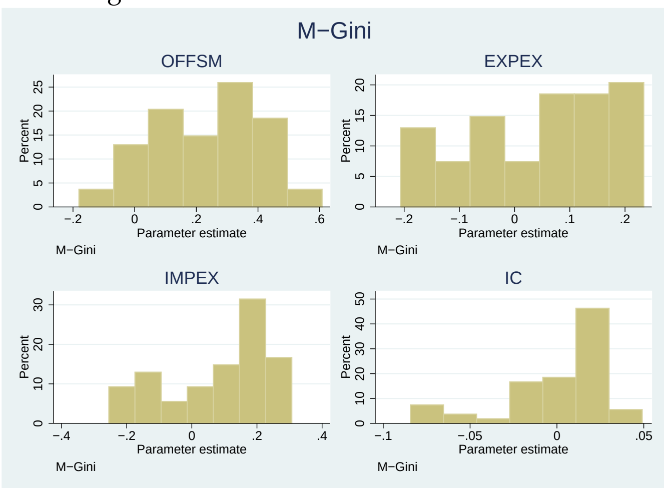
5.2.1 Descriptive Evidence

Distribution of the Coefficients

Figures 5.1 and 5.2 show the histograms of the globalization coefficients (β_1 in eq. 4.2) in the meta-database separately for net-market and disposable income Gini. Both histograms reveal substantial differences between the four globalization measures.

To begin with, the histograms of the globalization coefficients for M-Gini

Figure 5.1: Histogram of the Globalization Coefficients based on M-Gini



are displayed in figure 5.1. The larger part of the parameter-estimates for offshoring (OFFSM) is to the right-hand side of zero with very few negative values. The first peak in the observations of the OFFSM coefficients is around 0.15, and a second peak is between 0.3 and 0.4. This would translate into elasticities of

0.08 to 0.17. In the cases of EXPEX and IMPEX, there is a peak around 0.2, but both measures show also substantial negative values. The IC coefficients are clustered around zero or 0.05, although there are a few negative outliers.

Figure 5.2: Histogram of the Globalization Coefficients based on (DPI) Gini

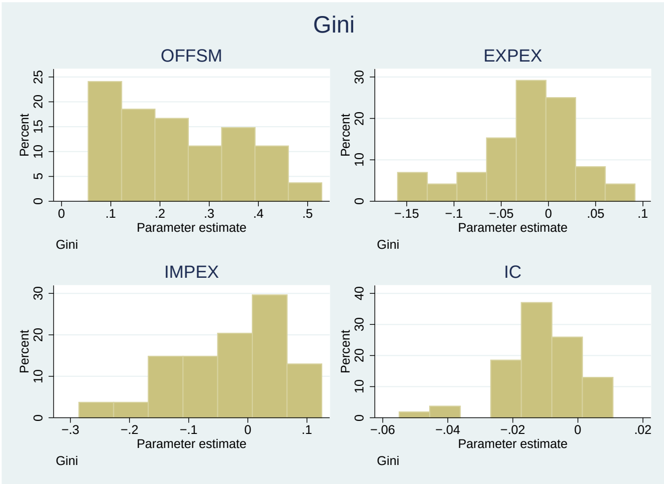


Figure 5.2 displays the estimates for disposable income inequality. A comparison with the net-market income findings reveals the following differences.

- None of the OFFSM coefficients is negative, and some of the estimates are even larger than in the net-market income case. This is surprising because the estimates were not standardized. Note, however, that the peak of the distribution is close to zero.

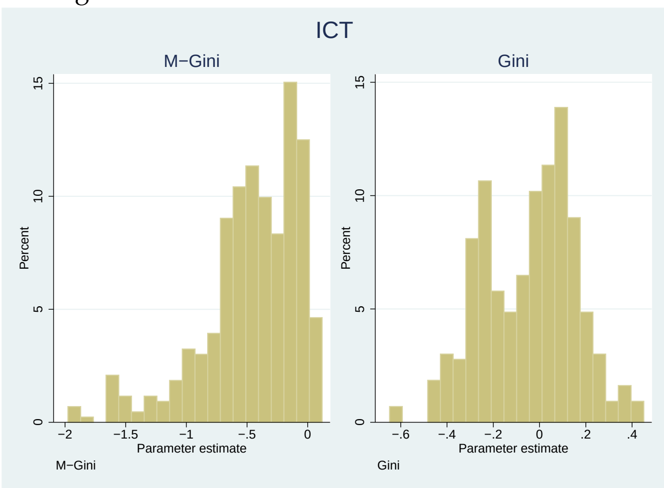
- The coefficients of the variables EXPEX, IMPEX and IC are now closely clustered around zero, although the larger part of the estimates turned out to be negative.

Overall, OFFSM seems to be the only globalization variable that shows positive impact on inequality independent of the specification. Interestingly, OFFSM is found to be even more robustly positively related to disposable than to net-market income inequality. This indicates that offshoring is somehow negatively correlated with (effective) redistribution, i.e., with the difference between (DPI) Gini and M-Gini.

The respective export and import coefficients display a more ambiguous pattern, especially in case of net-market income regressions. Clearly, the estimates have to be analyzed more extensively before it will be possible to draw conclusions from these observations.

The distribution of the ICT coefficients (β_2 in eq. 4.2) is displayed in figure 5.3. In the case of the disposable income Gini, there is a positive peak visible around 0.2 and a negative peak around minus 0.25. For net-market income inequality, the estimates are strongly skewed to the left, even though the highest peak of the distribution is near zero. This stands in contrast to the theoretical considerations and empirical findings on wage inequality from Feenstra and Hanson [9] among others, whereby offshoring and ICT coefficients are expected to have the same (positive) sign. A possible explanation for the negative sign

Figure 5.3: Histogram of the ICT Coefficients based on M-Gini and (DPI) Gini



is that ICT is an important growth factor (see Jorgenson [56]) and may cause lower inequality by increasing demand for less qualified labor.

Averages of the Coefficients

Table 5.1 displays the variance-weighted average coefficients (COEFF) of the globalization variables and of the information and communication technology variable ICT. Apart from the average marginal effects, the robustness of these results is indicated based on the corresponding (average) p-values (P-VAL). Thereby, (***) indicates a very robust result, i.e., the average p-value is smaller than 0.1, (*) stands for p-values smaller than 0.3 and (-) implies that significance is low, i.e., an average p-value larger than 0.3.

The weighted means of the globalization and technology coefficients and the indicators of the corresponding p-values are shown separately for the dependent variables of the underlying regressions - the three inequality measures Gini, MLD and P90P50 and disposable (columns 1-6) or net-market income (columns 7-12) - at a given time. The table is split into panels 1 - 3 to present the results for each of the three dummy settings ND, TD, CT (see table 4.3), as these have a strong impact on the size and significance of the coefficients.

Table 5.1: Weighted Average Coefficients of the Globalization Variables and of ICT

Dependent	Disposable Income						Net-market Income					
variable	Gini		MLD		P90P50		Gini		MLD		P90P50	
	COEFF	P-VAL	COEFF	P-VAL	COEFF	P-VAL	COEFF	P-VAL	COEFF	P-VAL	COEFF	P-VAL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel 1: ND - No (time) Dummies												
OFFSM	0.205	***	0.316	***	0.414	-	0.176	*	0.573	*	0.566	-
EXPEX	0.006	-	-0.00	-	0.118	-	0.106	***	0.180	-	0.383	*
IMPEX	-0.02	-	-0.12	*	0.289	-	0.169	*	0.280	-	0.871	*
IC	-0.00	-	0.008	-	-0.03	-	0.016	*	0.050	*	0.089	*
ICT	0.033	-	-0.10	-	0.535	*	-0.09	-	-0.48	*	-0.07	-
Panel 2: TD - Time Dummies												
OFFSM	0.253	***	0.433	***	0.416	-	0.115	-	0.408	*	0.257	-
EXPEX	-0.01	-	0.019	-	-0.04	-	-0.03	-	-0.29	*	-0.06	-
IMPEX	-0.05	-	-0.14	*	0.311	-	-0.01	-	-0.30	*	0.285	-
IC	-0.01	*	0.008	-	-0.07	*	-0.00	-	-0.01	-	0.015	-
ICT	-0.00	-	0.025	-	0.182	-	-0.31	***	-0.94	*	-1.19	*
Panel 3: CT - Time-Variable Country Dummies												
OFFSM	0.211	*	0.199	-	1.350	***	0.415	***	0.882	*	2.564	***
EXPEX	0.070	*	0.062	-	0.431	*	0.163	*	0.315	***	0.901	*
IMPEX	0.019	-	-0.06	-	0.315	-	0.137	*	0.145	*	0.487	*
IC	-0.00	-	-0.01	-	0.007	-	0.022	*	0.038	*	0.086	*
ICT	-0.23	*	-0.59	*	-1.36	*	-0.73	***	-3.01	***	-4.04	***

**** Average p-value smaller than 0.1, * Average p-value smaller than 0.3, - Average p-value equal to or larger than 0.3*

The main observations drawn from table 5.1 are as follows.

- The globalization variables are mostly positively related to inequality (on average), but the significance level seems rather poor at first glance. Of the four globalization variables, only OFFSM has a positive sign for all inequality measures and dummy specifications. Regarding the other three measures, no unambiguous conclusion can be drawn. Overall, the variable IC (import competition) shows the weakest results of all four variables.

- A comparison between DPI and MI-net based estimations shows substantial differences in the coefficients. With the exception of offshoring, the coefficients are on average less significant on DPI than on MI-net inequality. Surprisingly OFFSM has a more robust impact on disposable than on net-market income inequality. This indicates that offshoring is negatively correlated to redistribution and also confirms the observations made in the analysis of the preceding figures 5.1 and 5.2. However, this finding nearly disappears in panel 3 when controlling for country-specific time trends because transfer systems are strongly different across countries. With regard to the trade-based measures EXPEX and IMPEX, the signs of the coefficients do not change in the respective panels, but the p-values indicate a slightly better significance for MI-net than for DPI inequality.

- The coefficients are similar with respect to sign and significance for the three inequality measures - Gini, MLD and P90P50 - with some minor exceptions. For net-market income, the coefficients on the bottom-sensitive MLD show - in panel 2 - the best significance. This indicates that the impact of globalization is more pronounced on the lower parts of the income distribution.

- The dummy specification has a strong impact on the estimates. The introduction of time dummies (panel 2) reduces the size and significance of the coefficients on MI-net inequality. This is especially pronounced for EXPEX and IMPEX but holds as well for the remaining globalization variables. The coefficients based on DPI react more heterogeneously to the inclusion of time dummies but remain, on average, only weakly significant and close to zero. An exception is offshoring, where the coefficient even increases from panel 1 to panel 2. In contrast to time dummies, controlling for country-specific time trends (panel 3) strongly improves the significance of the globalization coefficients on net-market income inequality.

- With regard to ICT, a rather robust negative coefficient is found on net-market income inequality, as expected from figure 5.3. For disposable income inequality, on the other hand, the ICT coefficient is less stable. In most cases, it has a positive, although insignificant, sign, except for panel 3, where the coefficient turns negative as well.

To complete the picture, table 5.2 additionally displays the average parameter-estimates (ρ) for the remaining variables (CONTR) in equations 4.2. The structure of the table is identical to the preceding table 5.1.

Table 5.2: Weighted Average Coefficients of the Control Variables

Dependent	Disposable Income						Net-market Income					
variable	Gini		MLD		P90P50		Gini		MLD		P90P50	
	COEFF	P-VAL	COEFF	P-VAL	COEFF	P-VAL	COEFF	P-VAL	COEFF	P-VAL	COEFF	P-VAL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel 1: ND - No (time) Dummies												
IND-VA	-0.10	***	-0.07	*	-0.55	*	-0.17	***	-0.29	*	-1.17	***
AGR	0.167	*	0.247	***	0.644	*	0.104	-	0.172	-	0.844	-
AGE	-0.02	-	0.095	-	-0.45	-	0.183	*	1.293	***	1.522	*
PAT	-0.00	*	-0.00	*	-0.01	-	-0.01	*	-0.04	*	-0.04	*
UNION	-0.09	***	-0.04	*	-0.31	***	-0.15	***	-0.50	***	-0.91	***
Panel 2: TD - Time Dummies												
IND-VA	-0.08	*	-0.13	*	-0.38	*	-0.05	-	-0.08	-	-0.60	*
AGR	0.160	*	0.195	*	0.690	*	0.118	-	0.096	-	1.004	-
AGE	-0.02	-	0.048	-	-0.42	-	0.079	-	0.898	*	1.353	-
PAT	-0.00	-	-0.00	-	-0.00	-	-0.00	*	-0.04	*	-0.03	*
UNION	-0.10	***	-0.16	*	-0.27	***	-0.13	***	-0.67	***	-0.73	*
Panel 3: CT - Time-Variable Country Dummies												
IND-VA	-0.14	***	-0.17	***	-0.65	***	-0.15	*	-0.42	*	-0.98	***
AGR	0.132	*	0.177	***	0.587	***	0.100	*	-0.02	-	1.082	-
AGE	-0.29	***	-0.41	***	-1.07	*	-0.11	-	0.114	-	0.478	-
PAT	0.001	-	0.001	-	0.002	-	-0.00	***	-0.03	***	-0.02	*
UNION(1)	.	.	.	.	.	.	.	.	.	.	.	.

*** *Average p-value smaller than 0.1, * Average p-value smaller than 0.3, - Average p-value equal to or larger than 0.3*
(1) Note that UNION is a country level variable and therefore not included in Panel 3.

The main findings, listed by variable, are as follows.

- The share of industry value added relative to GDP (IND-VA) is negatively correlated to inequality, but is not highly significant. The relationship, however, is rather robust to the choice of inequality measure and dummy specification, and it holds before and after transfer payments. This confirms the evidence from several previously noted country studies (section 1.2.2) suggesting that deindustrialization increases household inequality.

- The share of agricultural employment (AGR) is positively related to DPI inequality. Interestingly, the coefficients turn insignificant in the case of net-market income inequality. It seems that rural regions either do less redistribution, or those regions become richer as the importance of agriculture declines, which may allow them to spend more on transfers.

- The variable AGE is rather unstable across specifications. In the case of net-market income inequality, the share of people older than 65 has a positive sign on the bottom-sensitive MLD. This possibly reflects the impact of public pensions, which are not part of net-market income.

- The number of patent applications (PAT) is negatively related to inequality, and the correlation seems rather robust across inequality variables and dummy specifications.

- The union share (UNION) is negative and very robustly related to inequality.

In summary, the averages of the control coefficients are in line with expectations from previous studies on inequality, despite the fact that the robustness of several variables is rather poor.

5.2.2 Meta-Regression Analysis

The preceding analysis indicates that offshoring (OFFSM) has a positive impact on inequality. This finding is robust to the underlying income specification or to the choice of inequality measure. By contrast, the other globalization variables - EXPEX, IMPEX and IC - are neither clearly positive nor negatively correlated to inequality. To this point, however, the analysis is incomplete. The low average significance levels, on one hand, and the ambiguous impact of the trade measures on inequality, on the other hand, are both sources of concern. Furthermore, the analysis revealed the strong impact of dummy settings on the significance and even the signs of the estimates. These specification effects are analyzed more systematically in the following.

To identify effects of the model specifications on the coefficients, several `meta-regressions` are run. The dependent variables of these regressions are the compiled globalization and technology coefficients (COEFF) in the meta-database (β_1 and β_2 in eq. 4.2). The independent variables are dummies for the specifications of the underlying regressions. The meta-regression looks as follows:

$$\mathrm{COEFF} = \alpha + \delta_{\mathrm{ND}} + \delta_{\mathrm{CT}} + \delta_{\mathrm{OLS}} + \delta_{\mathrm{REM}} + \delta_{\mathrm{BASIC}} + \delta_{\mathrm{FULL}} + \delta_{\mathrm{DPI}} + \epsilon \tag{5.1}$$

. The right-hand side of the meta-regression equation includes dummies for the respective specifications summarized in table 4.3, i.e., for the estimation methods (δ_{OLS}, δ_{REM}), the choice of dummy specification (δ_{ND}, δ_{CT}), sample size ($\delta_{\text{EU-4}}$), model setup (δ_{BASIC}, δ_{FULL}) and income specification (δ_{DPI}) of the underlying regressions. Note that the meta-database contains 324 estimated coefficients per globalization variable.
Given the not promising results, the variable IC is not included in the meta-regressions. Table 5.3 displays the results of the variance-weighted ordinary least squares regression on the estimated coefficients (eq. 5.1). The meta-regression is conducted separately for the coefficients of the three globalization indicators (columns 1 - 3) and of the technology indicator ICT (column 4)[1].

The findings are as follows.

METHOD The estimation method (δ_{OLS}, δ_{REM}) does not have a significant effect on the size of the offshoring coefficients. In contrast, the coefficients of EXPEX and IMPEX become smaller if the regression is based on OLS instead of REM or FEM. As shown in ICT (column 4), OLS and REM have a

[1]Note that the ICT coefficients are pooled from the regressions of the three respective globalization variables, i.e., based on 972 observations instead on 324.

Table 5.3: Meta-regression Results: Dependent Variables = Estimated Coefficients (COEFF) of Globalization Variables and ICT

Coefficients	OFFSM	EXPEX	IMPEX	ICT
	(1)	(2)	(3)	(4)
δ_{OLS}	.044	-.037***	-.077***	.045**
	(.039)	(.014)	(.023)	(.026)
δ_{REM}	.018	.017	.112***	.064***
	(.032)	(.012)	(.021)	(.022)
δ_{ND}	.089***	.053***	.059***	.068***
	(.032)	(.013)	(.022)	(.026)
δ_{CT}	.041	.130***	.092***	-.515***
	(.036)	(.014)	(.021)	(.031)
δ_{BASIC}	-.028	-.019*	-.033*	-.012
	(.030)	(.012)	(.019)	(.019)
δ_{FULL}	-.015	.019	.012	-.101***
	(.031)	(.012)	(.020)	(.021)
$\delta_{EU\text{-}4}$	.231***	-.035**	-.057***	-.001
	(.033)	(.014)	(.021)	(.021)
δ_{DPI}	.032	-.070***	-.148***	.28***
	(.027)	(.011)	(.018)	(.02)
CONST.	.122***	.041**	.055*	-.297***
	(.043)	(.018)	(.029)	(.031)
Obs.	324	324	324	972
R^2	.15	.352	.42	.39
F statistic	6.93	21.4	28.5	77

Notes: Standard errors in parentheses; * denotes significance at the 10 percent level; ** denotes significance at the 5 percent level; *** denotes significance at the 1 percent level.

positive effect, but because the average ICT coefficient is negative, larger coefficients imply estimates that are either closer to zero or are even turning positive.

DUMMY The coefficient size of the globalization variables reacts strongly on the dummy specification (δ_{ND}, δ_{CT}), as was already indicated in the preceding tables. The main message is, again, that coefficients become bigger if the regression includes no time dummies or time-variable country dummies.

MODEL The model specification (δ_{BASIC}, δ_{FULL}), i.e., the use of different sets of control variables, does not affect or only weakly affects the average coefficient size of the globalization variables. The ICT coefficient becomes more negative in the case of the full model setting, presumably due to the inclusion of the related technology variable PAT (the number of patent applications) in the regression.

SAMPLE If the (underlying) regression is run on the EU-4 sub-sample ($\delta_{\text{EU-4}}$), the coefficient of offshoring is significantly larger, while the coefficients of exports and imports are somewhat lower than in the full sample case.

INCOME The income measurement of the underlying inequality variables (δ_{DPI}) has a highly significant effect on export, import and ICT coefficients, resulting in lower trade and higher (less negative) ICT estimates (as has been shown in table 5.1).

Based on these findings, the incidence of negative coefficients of the trade-based globalization measures (EXPEX, IMPEX) can be explained. A negative coefficient occurs if the regression controls for an overall time trend but not for country-specific trends or if the cross-sectional information (in levels) remains in the data. Furthermore, regressions on the EU-4 sample are more likely to result in negative coefficients. In other words, regions within the EU-4 countries with higher than average levels of export intensities are likely to have lower income inequality. On the contrary, an above average increase of export intensity, relative to the respective country, causes a relative increase of inequality in the particular region, but given that income inequality is not very volatile in the short run, this result has less relevance even though the positive sign is highly significant.

To complement the analysis, meta-regressions on the p-values (P-VAL) of the estimated coefficients are also conducted:

$$\text{P-VAL} = \alpha + \delta_{\text{ND}} + \delta_{\text{CT}} + \delta_{\text{OLS}} + \delta_{\text{REM}} + \delta_{\text{BASIC}} + \delta_{\text{FULL}} + \delta_{\text{OFFSM}} + \delta_{\text{EXPEX}} + \delta_{\text{GINI}} + \delta_{\text{MLD}} + \epsilon \tag{5.2}$$

The regression equation (5.2) includes the same regressors as eq. 5.1, except (δ_{dpi}), and also includes additionally dummies for the respective globalization variable (δ_{OFFSM}, δ_{EXPEX}) and the inequality variable (δ_{GINI}, δ_{MLD}), of the underlying regression.
The regression results are shown in table 5.4. In the first two columns, the p-values of the three globalization coefficients are pooled. In column 1, the underlying regressions were run on DPI, in column 2, they were run on MI-net inequality. Columns 3 and 4 repeat the exercise for the ICT coefficients.

These first four columns (columns 1 to 4) show how the specification effects differ for the two income measurements of the underlying regressions and whether or not the selection of the globalization variable has an impact on the ICT coefficient. In addition, columns 5 - 8 in table 5.4 display the meta-regression results separately for each globalization variable and the technology indicator (as in table 5.3) to identify how the significance level of the coefficients (p-values) differs between the three inequality measures.

Overall, the results confirm the findings presented in table 5.3, but some new insights are gained as well. As it turns out, offshoring is less significantly correlated to upper income inequality (P90P50), while the significance levels of the remaining globalization variables do not show strong differences between the inequality measures. The offshoring indicator OFFSM is more strongly significant than the variables EXPEX and IMPEX on inequality measures based on disposable income. For net-market income, the significance levels of the globalization variables are not systematically different. Furthermore, in regressions including the variable OFFSM, the ICT coefficient has slightly less significance. This is not surprising in light of the close interdependence between the two measures.

With regard to further specification effects, the findings indicate the following differences between DPI and MI-net based regressions.

METHOD The method dummies (OLS, REM) in columns (1) and (2) show that only the net-market income-based coefficients differ significantly between the estimation methods. The results point to the presence of unobserved regional fixed effects in the MI-NET case.

DUMMY Both specifications ND and CT increase the significance of the globalization variables (compared to time-dummy specifications), indicating the presence of overall time trends in net-market income-based regressions.

MODEL The set of included control variables does not seem to have a systematic impact on the significance of the globalization variables (with some minor exceptions). ICT is less significant in the full model case.

SAMPLE The EU-4 sub-sample delivers better significance than the total sample. Specifically, the reduction of the underlying p-values for the variables OFFSM and ICT is highly significant (columns 5 and 8).

5.2.3 Summary

The complexity of the relationship between globalization and inequality is mirrored by the differing effects of the particular globalization variables on inequality and the presence of considerable specification effects. To summarize, the main findings for the primary variables of this analysis are the following.

OFFSM Offshoring increases inequality. This holds for net-market income but also, and more strongly, for disposable income inequality. The relationship is more distinct for the EU-4 than for the full sample. With regard to net-market income inequality, the coefficients become larger and more significant when the regression includes country-specific time dummies. One reason for this is the presence of opposing country trends (those of Spain and Greece).

Table 5.4: Meta-regression Results: Dependent Variables = P-Values of Globalization and ICT Coefficients.

P-Values	GLOBALIZATION(1)		ICT		OFFSM	EXPEX	IMPEX	ICT
	DPI(2)	MI-NET(3)	DPI(2)	MI-NET(3)	DPI & MI-NET(4)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
δ_{OLS}	.020	-.059**	.139***	-.002	-.037	.013	-.034	.068***
	(.031)	(.028)	(.031)	(.022)	(.033)	(.040)	(.039)	(.022)
δ_{REM}	-.030	-.161***	-.090***	.065***	-.137***	-.063	-.086**	-.013
	(.031)	(.028)	(.031)	(.022)	(.033)	(.040)	(.039)	(.022)
δ_{ND}	-.022	-.158***	-.094***	.220***	-.160***	-.057	-.052	.063***
	(.035)	(.031)	(.035)	(.025)	(.037)	(.044)	(.043)	(.024)
δ_{CT}	-.025	-.197***	-.169***	-.105***	-.118***	-.221***	.006	-.137***
	(.031)	(.028)	(.031)	(.022)	(.033)	(.040)	(.039)	(.022)
δ_{BASIC}	.051*	-.009	.037	-.008	.029	.031	.003	.015
	(.031)	(.028)	(.031)	(.022)	(.033)	(.040)	(.039)	(.022)
δ_{FULL}	.002	.052*	.049	-.081***	.042	-.012	.051	-.016
	(.031)	(.028)	(.031)	(.022)	(.033)	(.040)	(.039)	(.022)
$\delta_{EU\text{-}4}$	-.096***	-.085***	-.020	-.005	-.176***	-.006	-.090**	-.013
	(.031)	(.028)	(.031)	(.022)	(.033)	(.040)	(.039)	(.022)
δ_{OFFSM}	-.199***	-.035	-.043	.100***				
	(.031)	(.028)	(.031)	(.022)				
δ_{EXPEX}	.071**	-.019	-.011	.024				
	(.031)	(.028)	(.031)	(.022)				
δ_{GINI}					-.083**	-.047	.001	-.057***
					(.033)	(.040)	(.039)	(.022)
δ_{MLD}					-.068**	-.031	.021	-.019
					(.033)	(.040)	(.039)	(.022)
CONST.	.391***	.492***	.400***	.134***	.420***	.458***	.362***	.291***
	(.034)	(.031)	(.034)	(.024)	(.044)	(.053)	(.051)	(.024)
Obs.	486	486	486	486	324	324	324	972
R^2	.174	.173	.158	.373	.18	.114	.04	.112
F statistic	11.17	11.05	9.95	31.4	7.66	4.51	1.44	13.4

Notes: (1) Pooled p-values of the OFFSM & EXPEX & IMPEX coefficients. (2) Underlying regressions were based on DPI inequality or, (3), on MI-net inequality. (4) No distinction made between DPI and MI-net inequality.
Standard errors in parentheses; * denotes significance at the 10 percent level; ** denotes significance at the 5 percent level; *** denotes significance at the 1 percent level.

EXPEX / IMPEX The sign of the trade-based coefficients is ambiguous. The overall effect on net-market income inequality is negative, but the regional time variations relative to the respective countries reveal a hidden positive impact on inequality. Again, the relationships are more distinct for the EU-4 sample. EXPEX is, on average, more significant than the import variable IMPEX (and IC as well).

ICT Information and communication technology ICT has a rather robust negative coefficient on net-market income inequality measures. For disposable income, the results are ambiguous and less significant. In contrast to the globalization variables, the findings are not influenced by the sample choice.

The main insights regarding the model specifications are the following.

METHOD The effect of globalization on inequality is stronger and more robust in levels than in differences. An explanation for this is the presence of unobserved regional characteristics (fixed effects) correlated to inequality and to globalization, resulting in an omitted variable bias. Nevertheless, regression in levels may be preferable given the relatively low time-variation of income inequality.

SAMPLE The findings are more distinct and stable for the EU-4 than for the full sample. This is explained by the fact that in the latter, a group of rather heterogeneous countries - Mediterranean countries like Spain and Greece, on the one hand, and the very different Nordic countries on the other hand - join the sample. This emphasizes the difficulty of finding a model that controls for all the various special characteristics, even in an all-European sample.

INCOME The results provide evidence that redistribution does not automatically mitigate the impact of globalization on income distribution. In the case of offshoring, the correlation is even negative. This last finding, however, is mainly a country-level phenomenon and disappears after controlling for the country-specific trends. For trade based measures, the findings were similar but more pronounced on net-market as opposed to disposable income inequality.

5.3 A Benchmark Model

In this section, to address several open econometric issues and to conduct some sensitivity tests, a benchmark model is specified based on the insights of the meta-analysis. More specifically, this regression serves as a benchmark to analyze the role of GDP, the robustness of the main findings regarding different inequality measurement, possible endogeneity problems of the globalization variables and the interdependence of structural change and offshoring.

5.3.1 Specification

The following econometric model is considered:

$$\begin{aligned} \mathrm{GINI}_{it} = {} & \alpha + \beta_1\,\mathrm{OFFSM}_{it} + \beta_2\,\mathrm{ICT}_{it} + \beta_3\,\mathrm{IND\text{-}VA}_{it} + \beta_4\,\mathrm{AGR}_{it} + \\ & \beta_5\,\mathrm{PAT}_{it} + \beta_6\,\mathrm{UNION}_{it} + \mu_c + \gamma_t + (\mu_c\gamma_t) + \epsilon_{it} \end{aligned} \tag{5.3}$$

Offshoring is the main independent variable of the benchmark regression, given its more robust relationship to inequality in comparison with the remaining globalization measures. Regression 5.3 corresponds basically to the FULL model specification (see section 4.2.3), although the variable AGE is excluded due to its poor average significance indicated in the meta-analysis. In addition to country effects (μ_c), the regression controls for common time trends (γ_t) and for time-variable country effects ($\mu_c\gamma_t$), given their strong impact on the average coefficient size. This interaction term between country and time dummies is in parentheses because it is optional in the benchmark setting.

The Gini, as the most commonly applied inequality measure, is used as the main dependent variable. A comparison of the applied inequality measures is part of the robustness tests. The analysis is restricted to the EU-4 to ensure a more homogeneous sample, which is less prone to outliers and less influenced by country trends than is the case for the full sample.

5.3.2 Results and Robustness Analysis

All the previous results and conclusions are based on weighted means of estimated coefficients and on the results of meta-regressions. Now, table 5.5 reports the regression results based on equation 5.3. The regressions are primar-

ily estimated using OLS, as poolability is accepted at the 95% level given the use of country dummies. Furthermore, a Ramsey RESET test for no omitted variables is accepted at the 95% confidence level for columns 1-3 and for the GDP case (4).
The first three columns display the regression results for the benchmark model. This confirms that offshoring has a stronger positive impact on disposable income inequality (column 1) than on net-market income inequality (column 2). ICT is not significant on disposable income, in contrast to the share of industry value, which is more significant for DPI than for MI-net regressions. Column 3 is again based on net-market income, but now, interaction terms between time and country dummies are included[2]. The fit of the regression improves drastically from 0.63 in the benchmark specification to 0.71. The variable OFFSM becomes larger and highly significant, while the negative relationship of ICT to inequality becomes much stronger.
In column 4, GDP per capita (GDPC) (in logs) is included in the regression as a control variable. However, in light of the high correlations of PAT and AGR to GDPC, both of the former variables are dropped from the regression. The results show that GDP per capita is negatively correlated to net-market income inequality. Importantly, the OFFSM and ICT coefficients are virtually unchanged compared to column 3. That said, the explanatory power of the regression is now slightly weaker than with AGR and PAT included. This finding indicates that the economic growth is not a primary channel of the effects of globalization on inequality.

In all of the remaining columns 5-8, the regressions are also based on net-market income. Columns 5 and 6 are based on the same specification, but as a sensitivity test, the MLD in (5) and the P90P50 in (6) are applied as dependent variables. The results are similar to the Gini regression in (4), even though OFFSM is marginally less significant in the MLD case. The explanatory power of the regressions is also lower, with Rsq. 0.61 and 0.63 instead of 0.69.
In the final two columns 7-8, offshoring is treated as an endogenous variable. Due to the lack of reliable instruments, the regression is estimated using system GMM estimation (abbreviated as BB in table 5.5) instrumenting levels with

[2]Indicated as CT the time-variable country dummy in table 5.5

Table 5.5: Benchmark Regression Results and Robustness Analysis

Dep.Var.	Gini	M-Gini	M-Gini	M-Gini	M-MLD	M-P90P50	M-Gini	M-Gini
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OFFSM	.261***	.117	.493***	.486**	1.133	4.076***	.343*	.264**
	(.082)	(.117)	(.184)	(.196)	(.731)	(1.323)	(.197)	(.114)
ICT	-.002	-.591***	-1.572***	-1.455***	-6.062***	-8.138***	-1.200***	-.329**
	(.147)	(.181)	(.298)	(.325)	(1.341)	(2.683)	(.320)	(.168)
IND-VA	-.130***	-.049	-.085	-.108*	-.350*	-1.028***	-.102	-.079
	(.038)	(.053)	(.053)	(.057)	(.201)	(.327)	(.100)	(.079)
AGR	.082	.096	.109					
	(.063)	(.108)	(.090)					
PAT	-.0002	-.010***	-.008***					
	(.001)	(.003)	(.002)					
UNION	-.443***	-.473***						-.155
	(.111)	(.182)						(.190)
GDPC				-.045***	-.133**	-.192*	-.051**	-.047**
				(.016)	(.061)	(.104)	(.025)	(.022)
L.GINI								.383**
								(.144)
Const.	.437***	.670***	.588***	1.011***	2.759***	4.330***	1.067***	.781***
	(.063)	(.099)	(.054)	(.147)	(.527)	(.940)	(.219)	(.297)
Obs.	128	128	128	128	128	128	128	96
R^2	.697	.636	.712	.691	.616	.632	.	.
F statistic	24.24	20.71	18.59	19.28	16.07	20.02	41.24	57.09
Method	OLS	OLS	OLS	OLS	OLS	OLS	BB†	BB†
Dummy‡	TD	TD	CT	CT	CT	CT	CT	TD
Hansen Test§	.	.	.	.	.	.	.334	.165

Notes: Robust standard errors in parentheses; * denotes significance at the 10 percent level; ** denotes significance at the 5 percent level; *** denotes significance at the 1 percent level.
‡ TD = time and country dummies, CT = time-variable country dummies
† BB = Blundell and Bover GMM estimator.
§ Hansen J test statistic of overidentifying restrictions (Hansen [57]).

differences (Blundell and Bover [58]). The regressions use different dummy specifications, and in column 8 a lagged dependent variable is also included. Nonetheless, the coefficients on offshoring and on ICT remain significant if somewhat smaller than before.
The size of the coefficients can be interpreted as follows. The coefficients on OFFSM for net-market income inequality translate into elasticities between 0.17 and 0.25, i.e., a 10% increase in offshoring causes a rise in the Gini of between 1.7% and 2.5%. On the other side, a 10% rise in ICT reduces inequality between 1% and 2%. In summary it can be said, therefore, that the magnitude of the results ranges within a credible scope.

Results and Robustness Analysis for EXPEX

Although the regression model was specified specifically for offshoring, it can also be used to estimate the impact of different globalization indicators. To complete the analysis, the previous benchmark regression is used, with some adjustments, for the export share of manufacturing (EXPEX) instead of offshoring.

The regression is based on the benchmark equation 5.3, but OFFSM is substituted with EXPEX. Additionally, there is no focus on time-variable country dummies (CT), given the results of the meta-analysis. The goal here is, on the one hand, to address the questions of endogeneity and sensitivity to other inequality measures and, on the other, to better explain the incidence of the negative and positive signs of the EXPEX coefficient. All but the first regressions are run on net-market income inequality.

Table 5.6 presents the results for export intensity[3] EXPEX.
Columns 1 and 2 show the results of the benchmark specification for disposable (1) and net-market (2) income inequality. The regressions are based on the EU-4 sample and include time and country dummies. A Pesaran test[4] of cross-sectional independence is clearly accepted for this setup. A value of negative 1.3 for the EXPEX coefficient would translate into an elasticity of negative 0.1. In

[3]The results for imports are slightly less consistent, but essentially similar.
[4]The Breusch-Pagan LM test is not valid in a small T and large N context, see Pesaran [55]

column 3, the variables AGR and PAT are substituted with (log) GDP per capita GDPC. Columns 4 and 5 show regressions in which the dependent variable is now the MLD and the P90P50, respectively. The results are robust to different inequality measures, as documented in the next two columns. The estimated coefficients on the export intensity are also negative, but only statistically significant for the MLD. Moreover, the elasticity is quite a bit larger in magnitude, i.e., (negative) 0.3 for the MLD.

In column 6, the export intensity is treated as endogenous. The coefficients are estimated using the system GMM estimator (BB). The coefficient on EXPEX remains significant and negatively correlated to inequality. With regard to controls, (log) GDP per capita, the union share and the number of patent applications are, as before, significant.

The remaining three columns identify the specification under which positive coefficients on EXPEX - as indicated in figure 5.1 or table 5.3 - emerge. The regressions are estimated by FEM and use the EU-4 in (7) and the full sample size in (8) and (9). In column 8, the export coefficient is no longer significant, and the fit of the regression is drastically lower than in the comparable regression in column 7 for the EU-4. However, a highly significant positive coefficient emerges by including time-variable country dummies (CT), as shown in column 8.

Table 5.6: Regression Results and Robustness Analysis for EXPEX

Dep. Var.	Gini	M-Gini	M-Gini	M-MLD	M-P90P50	M-Gini	M-Gini	M-Gini	M-Gini
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EXPEX	-.016	-.114*	-.136*	-.776***	-.435	-.169*	-.150**	.0003	.178***
	(.052)	(.066)	(.072)	(.256)	(.411)	(.094)	(.064)	(.092)	(.054)
ICT	-.168	-.687***	-.572***	-2.155***	-2.132*	-.552***	-.495***	-.422***	-1.125***
	(.131)	(.160)	(.165)	(.559)	(1.194)	(.123)	(.116)	(.117)	(.257)
IND-VA	-.132***	-.035	-.052	-.121	-.662*	-.046	-.007	-.221*	-.365***
	(.039)	(.051)	(.058)	(.197)	(.339)	(.099)	(.102)	(.122)	(.094)
AGR	.040	.075							
	(.072)	(.098)							
PAT	-.0007	-.010***							
	(.002)	(.002)							
UNION	-.586***	-.482***	-.445***	-2.083***	-1.943	-.456***	-.399***	-.291***	
	(.103)	(.166)	(.162)	(.578)	(1.316)	(.115)	(.113)	(.105)	
GDPC			-.055***	-.173***	-.272***	-.059**	-.120**	.002	-.028
			(.016)	(.053)	(.097)	(.023)	(.052)	(.068)	(.035)
Const.	.537***	.723***	1.297***	3.790***	6.387***	1.265***	1.924***	.614	.866**
	(.049)	(.072)	(.151)	(.493)	(1.046)	(.230)	(.531)	(.669)	(.344)
Obs.	128	128	128	128	128	128	128	184	184
R^2	0.652	.643	.623	.535	.561	.	.59	.389	.629
F statistic	23.45	21.69	21.88	13.06	9.95	16.94	6.08	10.73	7.67
Method	OLS	OLS	OLS	OLS	OLS	BB†	FEM	FEM	FEM
Dummy‡	TD	TD	TD	TD	TD	TD	TD	TD	CT
Hansen-test§	.	.	.	.	.	0.134	.	.	.

Notes: Robust standard errors in parentheses; * denotes significance at the 10 percent level; ** denotes significance at the 5 percent level; *** denotes significance at the 1 percent level.
‡ TD = time and country dummies, CT = time-variable country dummies
† BB = Blundell and Bover GMM estimator.
§ Hansen J test statistic of overidentifying restrictions (Hansen [57]).

5.3.3 Structural Change and Offshoring

To this point, there has been no discussion of whether the impact of offshoring on inequality depends on the regional economic size of the manufacturing sector. The variable OFFSM measures the offshoring intensity of the manufacturing sectors. The reason that offshoring was set in relation to manufacturing and not to overall economy-wide employment or to GDP was to disentangle the effects of globalization and structural change. This section, however, asks if the impact of offshoring is stronger in regions with a relatively larger share of manufacturing employment.

A test of this question can be carried out by checking whether the relationship between offshoring and inequality is stronger in regions with a greater share of manufacturing employment. The basic strategy in the next set of regressions, then, is to interact the regional manufacturing employment share with globalization to see whether this additional variable results in statistically significant coefficients and improves the fit of the regressions.

The regressions are based on the benchmark model (equation 5.3) including an interaction between offshoring and manufacturing employment. Note that in the benchmark setup, the economic size of manufacturing is captured by the variable IND-VA, i.e., by the ratio of value-added relative to GDP. This variable is negatively correlated to inequality even though the significance of the coefficients was rather low, indicating that regions with large industry shares have more equal distributions of income. Given the decline of manufacturing in many European regions (as documented in table 3.1), this implies that deindustrialization increased inequality.

Now, as an adjustment to equation 5.3, the regression and the main interaction term (OFFSM X MFS) include the share of manufacturing employment (MFS)[5], instead of manufacturing value added (IND-VA), as employment and productivity changes may offset one another. The weak results for IND-VA in the previous section support this conclusion. Nevertheless, the variable is also applied and interacted with OFFSM as a robustness test.

Note that the variables OFFSM and the share of manufacturing employment

[5]Mean and standard deviation of MFS are given in table 4.1.

(MFS) are correlated neither in levels nor after within-transformation[6].

Table 5.7 shows the results of the regressions for several specifications. Two main results emerge from this table: First, the interaction term OFFSM X MFS is in all regressions negative and highly significant and second, offshoring and the manufacturing employment share (MFS) are individually positive related to inequality. The other variables keep the same coefficients as in the regressions without interaction term.

Column 1 of the table displays the benchmark setting with the manufacturing employment share added to the regression, both individually and interacted with openness. In column 2 GDP per capita (in logs) is included[7] to capture possible omitted growth effects. The fit of the regression rises somewhat from 0.57 to 0.59. Column 3 repeats the regression for the EU-4 sub-sample. The next column 4 show a regression based on FEM for the full sample. In column 5 the coefficients are estimated by REM and time-variable country dummies are included. The corresponding Sargan-Hansen test statistic is given in the last row indicating that the REM assumptions are not rejected. These stable results indicate that unobserved regional effects are not an issue.

In the last column 6 industry value added (IND-VA) is substituted for manufacturing employment as described above. The coefficients on the interaction term remain weakly significant, but the coefficients of both IND-VA and OFFSM are no longer significantly different from zero. The explanatory power of the regression is also lower compared to the case with MFS. This suggests that employment and productivity changes were offsetting each other with respect to the impact on inequality.

To quantify the results of this table, the estimated coefficients are evaluated at different points along the distribution of manufacturing employment. The coefficients in column 1 suggest that an increase in offshoring of around 10% would increase inequality around 0.2%, given a manufacturing employment of about the mean. If manufacturing employment was one standard deviation

[6]Spearman's rho of roughly negative 0.09 in levels and positive 0.01 after within-transformation. In both cases, a test for independence is clearly accepted

[7]The variables AGR and PAT are dropped from the regression due to collinearity issues.

Table 5.7: Regression Results for Structural Change and Offshoring. Dependent Variable = M-Gini

Dep. Var.	M-Gini					
	(1)	(2)	(3)	(4)	(5)	(6)
OFFSM X MFS	-2.410***	-2.077***	-2.333*	-2.366**	-2.926***	
	(.738)	(.763)	(1.329)	(1.155)	(.883)	
OFFSM X IND-VA						-1.411*
						(.774)
OFFSM	.447**	.325*	.539*	.443*	1.075***	.357
	(.192)	(.198)	(.297)	(.258)	(.212)	(.274)
ICT	-.633***	-.594***	-.567***	-.429***	-.420***	-.531***
	(.146)	(.148)	(.170)	(.115)	(.138)	(.153)
MFS	.470***	.355**	.411	.686***	.526***	
	(.179)	(.177)	(.300)	(.265)	(.202)	
IND-VA						.292
						(.205)
PAT	-.009***					
	(.002)					
AGR	.122*					
	(.065)					
UNION	-.394**	-.423**	-.387**	-.399***		-.430**
	(.173)	(.171)	(.184)	(.117)		(.180)
GDPC		-.040***	-.047**	-.109*	-.045**	-.068***
		(.015)	(.019)	(.059)	(.018)	(.014)
Const.	.568***	1.025***	1.029***	1.604***	.701***	1.304***
	(.138)	(.192)	(.183)	(.605)	(.172)	(.162)
Obs.	177	177	128	128	177	177
R^2	.612	.583	.634	.604		.567
Methods	OLS	OLS	OLS	FEM	REM	OLS
Dummy‡	TD	TD	TD	TD	CT	TD
Sample	FULL	FULL	EU-4	EU-4	FULL	FULL
Sargan-Hansen§	.	.	.	.	0.15	.

Notes: Robust standard errors in parentheses; * denotes significance at the 10 percent level;
** denotes significance at the 5 percent level; *** denotes significance at the 1 percent level.
‡ TD = time and country dummies, CT = time-variable country dummies
§ Sargan-Hansen test of overidentifying restrictions (fixed vs random effects) (see Arellano [59]).

below the mean, the same increase in offshoring would lead to an increase in inequality of 1 percentage point. For a region with manufacturing employment one standard deviation above the mean, the increase in offshoring would actually result in a decline in inequality of around 0.5%.

These results show that the impact of offshoring is not more pronounced in regions with a large manufacturing sector. On the contrary a lower share of manufacturing employment is associated with a stronger effect of offshoring on the income distribution. Or to put it in a less static fashion, the decline of manufacturing amplified the impact of offshoring.

To give further evidence, it would be necessary to analyze this finding in greater detail on the single industry level, which is unfortunately beyond the scope of the available data. That said, the results emphasize the importance that globalization or trade intensity be measured independently from the size of the manufacturing sector in a regression model for income inequality.

Chapter 6

Extension: Service Offshoring

..many service workers will also have to accept the new, and not very pleasant, reality that they too must compete with workers in other countries. And there are many more service than manufacturing workers..; Blinder [4]

6.1 Introduction

The preceding analysis discussed the impact of globalization on income inequality across European regions. The findings point to the conclusion that offshoring in manufacturing industries is positively related to income inequality. This chapter complements the research on offshoring by extending the focus to services. More specifically, the aim of the analysis is to construct a feasible indicator of regional service offshoring and to shed some light on the impact on unemployment.

Service offshoring, the sourcing of service inputs from abroad either from an affiliated or unaffiliated firm, has received a great deal of attention in the media and recently, in academic publications as well. Empirical research on service offshoring is motivated by the belief that it will be the next large source of trade growth in developed countries.
There is no doubt that tradability of services will increase strongly over the next decades as further improvements in information and communication technologies allow more and more service tasks to become tradable. Alan Blinder [4]

even called the phenomenon of service offshoring a second Industrial Revolution.

In view of the expectations of strong future growth in service offshoring, evidence about the experience up to now is certainly helpful in conducting the inevitable debate about negative effects on job security and income distribution.

6.2 Measuring Service Offshoring

The initial situation and preconditions are similar to those in chapter 3, but the procedure applied to estimate the overall offshoring intensity in manufacturing cannot be adopted directly. Although service offshoring may also affect manufacturing productivity or employment, the main impact is presumably felt in service industries. Therefore, measuring service offshoring only in manufacturing - as done for example in Crino [60] - is not appropriate in this context. Instead, the degree service offshoring has to be measured on a economy-wide scale including all sectors.

The level of service offshoring (TSO)

$$\text{TSO} = \sum_{s \in S} \left(\frac{\text{total import of service inputs s}}{\text{total use of service inputs s}} \right)$$

is approximated by the share of imported service inputs relative to total service inputs for the whole economy, where the service sector S includes telecommunication, finance, computing, research and business services (NACE 64-67,71-74). The necessary data are drawn from the OECD Input-Output database for all countries and years. As mentioned in chapter 3, this kind of measure underestimates the level of service offshoring because previously in-house-produced service inputs that are offshored are not captured.

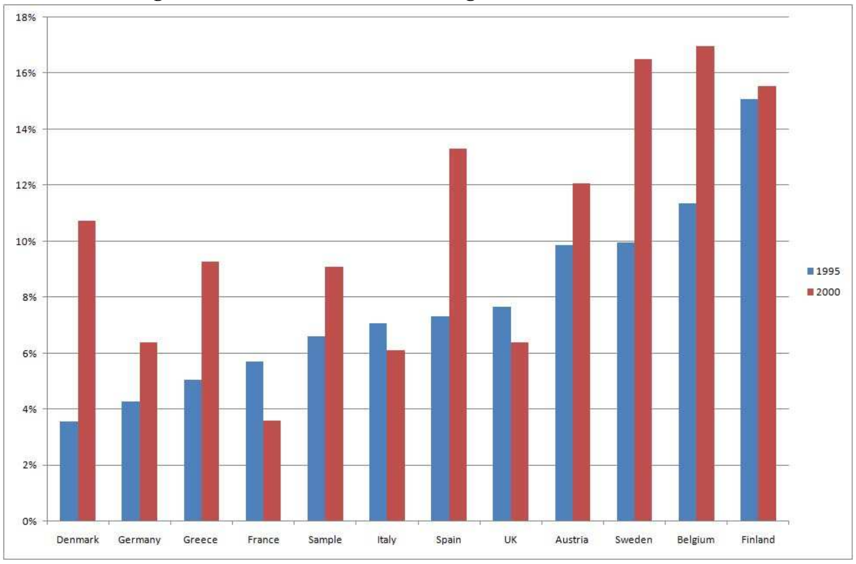
The variable TSO (total service offshoring) is a country-level variable. A regionalization is not feasible as there are no sufficiently disaggregated service employment figures available. To estimate the regional impact, it is interacted with the regional employment share of *high-technology sectors*[1]. The reasoning

[1]Source: Eurostat *htec_emp_reg* series - knowledge-intensive high-technology services: NACE Rev. 1.1 codes 64, 72, 73, i.e., employment in telecommunication, computing and research.

behind this is that service offshoring relies on the availability of a highly skilled service workforce to organize the offshoring process.

Figure 6.1 displays the resulting service offshoring intensities by country and year. On average, around 7% of the service (S) inputs were imported. Sweden, Finland and Belgium show the highest values, followed by Austria and Spain. Service offshoring increased in most countries, but there are also some exceptions, notably France, the UK and Italy, where a decline is observable.

Figure 6.1: Service Offshoring (TSO): 1995 and 2000



6.3 Service Offshoring and Unemployment

6.3.1 Motivation and Literature

This chapter deviates from the primary research focus of this study in that the econometric analysis does not focus on the impact on inequality, but on unemployment. In light of the stir about actual and potential job loss, the focus on unemployment rather than on income distribution seems promising at this time more and is potentially easier to identify, given that the actual impact is presumably rather small to date.

A review of the actual empirical research on service offshoring supports this effort. On the one hand, there are several empirical contributions asking how large the phenomenon can become. These studies point out that there is a huge number of potential offshorable service jobs (e.g., Bardhan and Kroll [61], Jensen and Kletzer [62] and Van Welsum and Vickery [63]). In light of the high probability that service offshoring will continue to grow in the near future and over the coming decades, there seems to be a lot to worry as a consequence.
On the other hand, several studies indicate that the number of jobs actually offshored is small thus far, at least relative to total job turnover (e.g., Kirkeegaard [1], Mankiw and Swagel [2]). Amiti and Wei find in case studies for the UK [64] and the US [65] that service offshoring has had only a marginal employment based on manufacturing data. Similarly, Liu and Trefler [66] find only a small impact on employment by matching US population survey data with trade data. These findings indicate that the impact of service offshoring is negligible, at least for now.
With regard to productivity, however, several studies find a positive impact of service offshoring. Using manufacturing panels, Amiti and Wei [67] for the US and UK, Gorg and Hanley [68] for Irish manufacturing[2] and Crino [60] for a sample of several European countries all find a significant positive impact of service offshoring on total factor productivity. These findings indicate that the positive effects on productivity more than offset possible negative employment impacts. In a theoretical contribution, Mitra and Ranjan [69] come to the similar conclusion that the positive productivity impact of service offshoring can be expected to produce a negative impact on unemployment.
All of the available studies were based on industry-level evidence but inevitably suffer from insufficient data disaggregation[3]. To focus instead on regional data may help to identify better evidence on the impact of service offshoring.
I am not aware of any attempts to measure the cross-national or even cross-regional impact of service offshoring on unemployment up to now.

[2] They only found a positive impact on exporting industries.
[3] See Krugman [3] for a discussion of the problem for similar data.

Table 6.1: Descriptive Statistics for Applied Variables

		Mean	St. Dev.	Min.	Max.	Change p.a.
		Year 2000				1995-2000
UNEMP	Unemployment rate	0.093	0.051	0.023	0.231	-2.8%
TSO	Total service offshoring	0.091	0.078	0.035	0.613	7.3%
HT-EMP	High-tech. employment share	0.031	0.013	0.009	0.064	4.1%
INV	Investment share into service sectors	0.371	0.125	0.091	0.569	2.2%
ICT	ICT in manufacturing	0.122	0.043	0.027	0.211	4.5%
GDPC	GDP per capita	23'406	8'490	10'321	50'425	2.7%
IND-VA	Share of industry value added	0.241	0.063	0.089	0.379	-1.7%
AGR	Agricultural employment share	0.05	0.059	0	0.319	-4.1%
UNION	Union share	0.287	0.153	0.1	0.79	-1.8%

6.3.2 Econometric Analysis

Overall, the data for the econometric analysis are available in the form of a balanced panel based on 61 regions and two time periods 1995 and 2000.

A brief description and summary statistics of the applied variables are shown in table 6.1. The for the first time[4] applied variables - regional unemployment rates (UNEMP), high-tech employment share (HT-EMP) and the investment share into services sectors[5] (INV), are available from Eurostat.

An analysis of the full 1985 - 2000 time period, as done in the preceding econometric framework, does not seem promising, given that service offshoring is a rather recent phenomenon. Therefore, this study focuses on the 1995 - 2000 time period. An extension to 2005 would certainly be helpful, but data availability makes coverage of the EU up to 2005 difficult. The regional database on inequality and globalization is used to identify if and how unemployment and service offshoring are correlated on the regional level.

The econometric analysis is based on a slightly adjusted version of benchmark regression 5.3:

$$\begin{aligned}\mathrm{UNEMP}_{it} = \alpha &+ \beta_1(\mathrm{TSO}_{it} * \mathrm{HT\text{-}EMP}_{it}) + \beta_2\mathrm{TSO}_{ct} + \beta_3\mathrm{HT\text{-}EMP}_{it} + \beta_4\mathrm{INV}_{it} \\ &+ \beta_5\mathrm{ICT}_{it} + \beta_6\mathrm{IND\text{-}VA}_{it} + \beta_7\mathrm{AGR}_{it} + \beta_8\mathrm{UNION}_{it} + u_{it}\end{aligned}$$

The variable service offshoring TSO is a country-level variable and is therefore interacted with the employment share of high-technology sectors. In addition to the technology share in manufacturing (ICT), the regression includes an in-

[4]HT-EMP and INV are only available since 1995.

[5](NACE 65-74: finance, computing, research and business services

dicator (INV) for the share of capital investment relative to overall investment in private sector service industries that are relevant for service offshoring instead of the number of patent applications (PAT). The error term is specified as $u_{it} = \eta_c + \gamma_t + \epsilon_{it}$, where η_c captures country-specific effects, γ_t picks up overall time effects, and ϵ_{it} is the i.i.d. error term. The full model will be estimated by ordinary least squares and by a fixed effect specification. In both cases, time dummies are included. In all estimations, the standard errors are robust to heteroskedasticity and are allowed to cluster within countries.

6.3.3 Results

Table 6.2 reports the regression results. Column 1 shows the full regression results; column 2 gives the results for a reduced model where the statistically insignificant structural variables IND-VA and AGR are dropped from the regression. In column 3, the reduced test equation is re-estimated using fixed effect estimation instead of least squares. Consequently, the fit of the regression improves strongly from .58 to .71. GDP per capita (in logs) is included only in the final two columns of table 6.2 as an explanatory variable. This allows estimation of the full effect of the variables of interest, including possible growth effects. This seems reasonable, given the evidence of the productivity effects of service offshoring. The results provide some support for the conjecture that service offshoring reduces unemployment. Even though the interaction term between total service offshoring and high-technology employment has a positive sign, the marginal effect of TSO is negative for all values of HT-EMP. The interaction term is no longer significant if the estimation is based on FEM. This indicates that omitted region-specific effects that bias the results with regard to HT-EMP are present.

Concerning the control variables, the service investment share (INV) is positive and very robustly related to unemployment. ICT, (log) GDPC and UNION are all robustly negatively correlated to the unemployment rate. The share of agricultural employment (AGR) and the share of industry value added to GDP (IND-VA) show no explanatory power. The inclusion of GDP per capita as an explanatory variable makes ICT insignificant and reduces the high-technology employment HT-EMP coefficient strongly but otherwise has no impact on the

Table 6.2: Regression Results: Dependent Variable = Unemployment Rate

	(1)	(2)	(3)	(4)	(5)
TSO X HT-EMP	21.041***	21.845**	6.177	21.918*	6.418
	(7.905)	(8.721)	(7.435)	(11.373)	(6.146)
TSO	-1.250***	-1.454***	-.973**	-1.281***	-.852***
	(.381)	(.324)	(.385)	(.352)	(.282)
HT-EMP	-3.573***	-3.194***	-.537	-2.031*	-.251
	(.945)	(.995)	(1.044)	(1.184)	(.804)
INV	.181**	.232**	.218***	.230***	.193***
	(.087)	(.091)	(.031)	(.083)	(.022)
ICT	-.402**	-.524***	-.571***	-.245	-.498***
	(.204)	(.197)	(.164)	(.197)	(.136)
GDPC				-.094**	-.215***
				(.038)	(.078)
IND-VA	-.246				
	(.156)				
AGR	.029				
	(.110)				
UNION	-.007**	-.007***	-.006**	-.007*	-.005**
	(.003)	(.002)	(.003)	(.004)	(.002)
CONST.	.331***	.269***	.339***	1.132***	2.431***
	(.067)	(.057)	(.087)	(.364)	(.789)
Obs.	118	118	118	118	118
R^2	.633	.579	.716	.683	.776
Method	OLS	OLS	FEM	OLS	FEM
Dummy‡	TD	TD	TD	TD	TD

Notes: Standard errors adjusted for intra-country correlations in parentheses; * denotes significance at the 10 percent level; ** denotes significance at the 5 percent denotes level; *** significance at the 1 percent level. ‡ TD = time and country dummies service offshoring coefficients.

Quantitatively, the reduced model in column 2 indicates that a 10% increase in service offshoring, given the average level HT-EMP, results in a decline in the unemployment rate of about 0.7%. Given values of HT-EMP one standard deviation above the mean, the findings indicate an unemployment decline of about 0.4%. As the increase of average service offshoring was around 30% between 1995 and 2000, this is clearly too strong and points to the possible presence of omitted time-variable country variables.

6.4 Concluding Comments

The data confirm that service offshoring has been growing strongly in the past. Unfortunately, a direct regionalization, based on the methodology applied in chapter 3, is not possible due to insufficiently disaggregated service employment statistics.

The analysis of the relationship between service offshoring and income distribution strongly suggests that there is no evidence linking service offshoring to higher unemployment. On the contrary, the findings indicate that regions that are more exposed to service offshoring have lower unemployment rates. However, given the limited time period of the analysis, the results should be interpreted with caution with regard to predictions of future developments.

Chapter 7

Summary and Conclusions

The role of globalization in shaping income distribution is an intensely debated topic in academic and public circles. However, despite the importance of this question for the public perception of globalization and, thereby, for the support of trade liberalization, there is no consensus on the effect on inequality. The available empirical evidence does not allow one to draw unambiguous conclusions, but in light of the complexity of the question and the different focal points of the relevant studies, this comes as no surprise.

This dissertation reinvestigates the relationship between globalization and income distribution. It proposes two main adjustments to previous studies to improve the reliability of the estimations. These are (i) to conduct the empirical analysis based on regional globalization intensities and inequality measures in a relatively homogeneous economic area (the European Union) and (ii) to estimate the effects of globalization on *net-market*, instead of solely on *disposable* income inequality.

(i) The empirical exploitation of regional values of inequality and globalization allows a more precise estimation than a mere cross-country analysis. In the latter, all sub-national heterogeneity is averaged out, and in the worst case, opposing trends between regions may offset each other.

(ii) The different transfer systems across Europe make the identification of the effects of globalization on inequality difficult. To deal with this problem, a separate analysis is conducted for net-market and disposable income inequality. This allows me to determine whether transfer-based redistribution mitigates the impact of globalization on inequality.

The main challenge to implementing these propositions is the lack of feasible data. One of the main contributions of this dissertation, then, is to compile a consistent database of inequality and globalization variables across European regions.

- The intra-regional inequality measures are calculated based on survey data compiled by the Luxembourg Income Study. This data source allows one to obtain feasibly consistent regional figures across time and countries.

- Due to the lack of comparable and consistent regional data on globalization, the required indicators are constructed based on a top-down approach and using available data sources. Thereby, country-level data on trade and offshoring are combined with regional manufacturing employment figures.

The descriptive evaluation of these measures reveals substantial gaps between the lowest and highest levels of both regional inequality and globalization within larger countries and emphasizes the importance of taking regional heterogeneity into account. These data on globalization and inequality build the basis for the subsequent investigation.

The econometric procedure is challenging because there is neither an established econometric model available to rely upon nor are the variables to be applied in such a framework clearly specified. As a further difficulty, the regional inequality and globalization data have the disadvantageous feature of being less reliable than their country-level counterparts.

To deal with these issues, a meta-analysis of globalization coefficients is done. Therefore, a meta-database of regression coefficients, estimated by the author, is compiled based on a large number of regressions using various model settings and specifications drawing on the regional inequality and globalization data.

This procedure allows for an assessment of the stability of the findings and the identification of possible specification effects. Overall, the meta-analysis techniques prove very helpful in eliminating spurious findings and allow for efficient identification of the most robust results and best specifications.

The results reflect the ambiguity of the findings in the empirical literature with regard to the impact of globalization, but they clearly indicate that offshoring behaves very differently from export- and import-based openness measures. The analysis shows that an increase in the intensity of offshoring makes the income distribution less equal. This finding is rather robust across model specifications, with the caveat that it applies much more strongly to the EU-4 regions than to the overall EU-15[1]. Interestingly, "effective" redistribution, i.e., the difference between disposable and net-market income inequality, is weaker in regions with higher offshoring intensity. An implication of this is that the transfer system fails to mitigate the impact on income distribution.
Regarding the trade-based measures, the results give no univocal picture. They show a negative relationship to inequality, in accordance with the findings of Jaumotte et al. [21], but when country trend effects are incorporated into the model, the relationship between export and import intensity and inequality turns positive. This suggests that country-specific time-variant omitted variables bias the coefficients. It is also possible that a negative relationship on the country level coexists with a regionally positive one. The use of net-market income inequality delivered similar but more robust results than did disposable income inequality. Furthermore, a comparison of bottom and top income-sensitive inequality measures indicated that the impact is more pronounced on the lower parts of the income distribution.

As a further finding, the results reported in this dissertation challenge the belief that ICT contributed to a rise in inequality. At least for Europe, the evidence considered here suggests, on the contrary, that technology is responsible for a decrease in net-market income inequality. In other words, the regional data give no evidence of a skill-bias of technological change. The most likely explanation is that ICT, as an important growth factor, helps to reduce unemployment and thereby net-market income-based inequality. This interpretation receives support from the finding that ICT is less statistically significant with

[1] without Portugal and the Netherlands

regard to disposable income inequality.

As an extension and to complement the findings on offshoring in manufacturing, I test the hypothesis that service offshoring may be responsible for increasing unemployment. Service offshoring is still in its infancy but, by all predictions, will be growing very fast over the next decade and will be the next important trend in globalization.
Some preliminary findings point to the conclusion that in case of market services[2], there are no negative employment effects. Service offshoring appears, in fact, to be correlated negatively to unemployment.

The negative public perception of globalization (and especially of offshoring) outlined at the beginning of this study is supported by the robust results for offshoring. Any conclusions must be put into perspective, however, given the mostly negative findings for trade-based measures and the opposite signs for offshoring and technology, which may offset one another.
At the moment, it is difficult to draw general policy conclusions based on the findings, as there are substantial differences between the economic openness measures regarding the impact on inequality.
An important implication of the results is that the effectiveness of the welfare systems in compensating losers from globalization is low. Hence, region-specific transfer payments may be helpful to keep public support in favor of further progress in economic globalization.

This study shows the advantage of regional analysis in assessing the impact of a global phenomenon like globalization. The findings demonstrate how the consideration of regional heterogeneity in larger countries can produce different conclusions than regular cross-country analysis. Given the substantial regional differences within most European countries, a pure country-based focus is likely not suitable to estimate the impact of globalization on inequality.
At the same time, however, the analysis also pointed out the weaknesses of the approach. The substantial data deficiencies - measurement errors in the inequality and globalization data - and omitted variables can distort the find-

[2]Excluding trade, transport, tourism and personal services

ings. The differences in the results for the EU-4 countries and the more heterogeneous full sample are an indication of just how important a careful econometric assessment of the relationship between globalization and inequality is. Despite these difficulties, it is possible to identify robust results beneath the noise in the data with the aid of meta-analysis techniques.

For future research, a robust theoretical framework would be especially helpful as a basis to better identify the connections between globalization and inequality. Furthermore, the use of more sophisticated methods to measure the regional intensity of offshoring and of final-goods trade may yield a high payoff. Additionally, and less demanding, an extension of the research focus up to the present date seems a worthy goal, as regional coverage and quality of the necessary data has improved considerably in the last few years.

Overall, this analysis provided a first step toward a better understanding of the role of globalization and technological progress in shaping income distribution. It has shown that additional information gained by a regional approach can substantially improve the empirical evidence and lead to different conclusions, while at the same time, it has also stressed that a more sophisticated framework and an improved database are necessary to arrive at final answers and definite policy recommendations.

Data Appendix

Table 7.1: Net-market Income Gini Coefficients

Name	NUTS	Country	1985	1990	1995	2000
Berlin (west)	de3	DE	0.41	0.38	0.39	0.50
Schleswig-Holstein	def	DE	0.39	0.36	0.39	0.45
Hamburg	de6	DE	0.49	0.40	0.44	0.51
Niedersachsen	de9	DE	0.42	0.38	0.41	0.44
Bremen	de5	DE	0.63	0.47	0.53	0.53
Nordrhein-Westfalen	dea	DE	0.42	0.39	0.42	0.44
Hessen	de7	DE	0.45	0.38	0.46	0.47
Rheinland-Pfalz + Saarland	deb+dec	DE	0.42	0.37	0.43	0.42
Baden-Wuerttemberg	de1	DE	0.38	0.35	0.39	0.40
Bayern	de2	DE	0.41	0.37	0.39	0.43
North Cumbria	ukc + ukd1	UK	0.48	0.47	0.52	0.53
Yorks Humberside	uke	UK	0.47	0.47	0.50	0.50
North West	ukd-ukd1	UK	0.46	0.49	0.51	0.49
East Midlands	ukf	UK	0.46	0.44	0.48	0.45
West Midlands	ukg	UK	0.47	0.49	0.48	0.48
East Anglia	ukh1	UK	0.43	0.40	0.48	0.45
Greater London	uki	UK	0.47	0.50	0.52	0.52
South East exc London	ukj+ukh2+ukh3	UK	0.41	0.40	0.45	0.44
South West	ukk	UK	0.43	0.43	0.45	0.46
Wales	ukl	UK	0.46	0.48	0.52	0.50
Scotland	ukm	UK	0.48	0.50	0.49	0.50
Nord Ovest	itc	IT	0.38	0.36	0.43	0.44
Nord Est	itd	IT	0.44	0.39	0.41	0.42
Centro (IT)	ite	IT	0.40	0.36	0.40	0.41
Sud (IT)	itf	IT	0.44	0.39	0.46	0.52
Isole (IT)	itg	IT	0.47	0.43	0.50	0.54
Île de France	fr1	FR	0.41	0.41	0.44	0.43
Bassin Parisien	fr2	FR	0.46	0.44	0.46	0.47
Nord - Pas-de-Calais	fr3	FR	0.49	0.52	0.50	0.51
Est	fr4	FR	0.45	0.44	0.44	0.42
Ouest	fr5	FR	0.46	0.47	0.47	0.47
Sud-Ouest	fr6	FR	0.49	0.49	0.49	0.47
Centre-Est	fr7	FR	0.43	0.44	0.45	0.47
Méditerranée	fr8	FR	0.47	0.52	0.51	0.54
Flandern	be2	BE	0.39	0.39	0.39	0.42
Wallonia	be3	BE	0.46	0.50	0.49	0.48
Brussel	be1	BE	0.41	0.33	0.38	0.51
Noroeste	es1	ES	-	-	0.53	0.47
Noreste	es2	ES	-	-	0.45	0.44
Comunidad de Madrid	es3	ES	-	-	0.42	0.41
Centro (ES)	es4	ES	-	-	0.51	0.50
Este	es5	ES	-	-	0.48	0.46
Sur	es6	ES	-	-	0.53	0.44
Canarias (ES)	es7	ES	-	-	0.48	0.47
Greek	gr1	GR	-	-	0.47	0.47
Greek	gr2	GR	-	-	0.47	0.49
Greek	gr3	GR	-	-	0.43	0.41
Greek	gr4	GR	-	-	0.46	0.41
Finland	Fi	FI	0.29	0.30	0.36	0.45
Denmark	Den	DEN	0.39	0.43	0.43	0.41
Luxembourg	Lux	LU	0.38	0.37	0.38	0.42
Ireland	Ir	IE	-	-	0.49	0.44
Austria Ost	Aus1	AT	-	-	0.45	0.44
Austria Sd	Aus2	AT	-	-	0.45	0.42
Austria West	Aus3	AT	-	-	0.43	0.40
Sweden	Swe	SE	-	-	0.47	0.45
Mecklenburg-Vorpommern	de8	DE	-	-	0.42	0.47
Brandenburg	de4	DE	-	-	0.42	0.48
Sachsen-Anhalt	dee	DE	-	-	0.45	0.52
Thüringen	deg	DE	-	-	0.42	0.48
Sachsen	ded	DE	-	-	0.43	0.46

Table 7.2: Disposable Income Gini Coefficients

Name	NUTS	Country	1985	1990	1995	2000
Berlin (west)	de3	DE	0.24	0.24	0.27	0.27
Schleswig-Holstein	def	DE	0.25	0.23	0.28	0.27
Hamburg	de6	DE	0.29	0.22	0.23	0.3
Niedersachsen	de9	DE	0.26	0.25	0.27	0.26
Bremen	de5	DE	0.23	0.25	0.27	0.27
Nordrhein-Westfalen	dea	DE	0.27	0.27	0.29	0.27
Hessen	de7	DE	0.29	0.24	0.29	0.29
Rheinland-Pfalz + Saarland	deb+dec	DE	0.26	0.25	0.26	0.25
Baden-Wuerttemberg	de1	DE	0.26	0.26	0.26	0.25
Bayern	de2	DE	0.26	0.27	0.28	0.26
North & Cumbria	ukc + ukd1	UK	0.29	0.3	0.36	0.36
Yorks & Humberside	uke	UK	0.28	0.32	0.32	0.33
North West	ukd-ukd1	UK	0.28	0.34	0.34	0.33
East Midlands	ukf	UK	0.3	0.3	0.35	0.34
West Midlands	ukg	UK	0.28	0.34	0.32	0.33
East Anglia	ukh1	UK	0.27	0.29	0.33	0.32
Greater London	uki	UK	0.33	0.39	0.37	0.39
South East exc London	ukj+ukh2+ukh3	UK	0.31	0.31	0.34	0.34
South West	ukk	UK	0.29	0.32	0.33	0.34
Wales	ukl	UK	0.28	0.3	0.34	0.32
Scotland	ukm	UK	0.31	0.32	0.32	0.32
Nord Ovest	itc	IT	0.3	0.26	0.31	0.3
Nord Est	itd	IT	0.3	0.28	0.3	0.3
Centro (IT)	ite	IT	0.29	0.26	0.29	0.28
Sud (IT)	itf	IT	0.33	0.28	0.34	0.36
Isole (IT)	itg	IT	0.35	0.31	0.36	0.39
Île de France	fr1	FR	0.3	0.29	0.31	0.29
Bassin Parisien	fr2	FR	0.3	0.26	0.26	0.26
Nord - Pas-de-Calais	fr3	FR	0.29	0.27	0.26	0.28
Est	fr4	FR	0.28	0.26	0.26	0.23
Ouest	fr5	FR	0.28	0.28	0.27	0.25
Sud-Ouest	fr6	FR	0.31	0.28	0.28	0.26
Centre-Est	fr7	FR	0.29	0.29	0.27	0.26
Méditerranée	fr8	FR	0.3	0.32	0.29	0.29
Flandern	be2	BE	0.22	0.23	0.22	0.24
Wallonia	be3	BE	0.23	0.24	0.24	0.25
Brussel	be1	BE	0.25	0.23	0.23	0.31
Noroeste	es1	ES	-	-	0.34	0.31
Noreste	es2	ES	-	-	0.32	0.3
Comunidad de Madrid	es3	ES	-	-	0.33	0.31
Centro (ES)	es4	ES	-	-	0.35	0.34
Este	es5	ES	-	-	0.34	0.34
Sur	es6	ES	-	-	0.36	0.3
Canarias (ES)	es7	ES	-	-	0.35	0.35
Voreia Ellada	gr1	GR	-	-	0.36	0.33
Kentriki Ellada	gr2	GR	-	-	0.35	0.34
Attiki	gr3	GR	-	-	0.31	0.3
Nisia Aigaiou, Kriti	gr4	GR	-	-	0.35	0.3
Finland	Fi	FI	0.21	0.21	0.22	0.25
Denmark	Den	DEN	0.28	0.26	0.22	0.23
Luxembourg	Lux	LU	0.28	0.28	0.24	0.26
Ireland	Ir	IE	-	-	0.34	0.31
Austria Ost	Aus1	AT	-	-	0.34	0.33
Austria Sd	Aus2	AT	-	-	0.34	0.3
Austria West	Aus3	AT	-	-	0.34	0.31
Sweden	Swe	SE	-	-	0.22	0.25
Mecklenburg-Vorpommern	de8	DE	-	-	0.23	0.25
Brandenburg	de4	DE	-	-	0.24	0.23
Sachsen-Anhalt	dee	DE	-	-	0.24	0.23
Thüringen	deg	DE	-	-	0.2	0.22
Sachsen	ded	DE	-	-	0.2	0.22

Table 7.3: Export Intensity Data: EXPEX

Name	NUTS	Country	1985	1990	1995	2000
Berlin (west)	de3	DE	0.22	0.25	0.35	0.46
Schleswig-Holstein	def	DE	0.23	0.24	0.31	0.46
Hamburg	de6	DE	0.22	0.25	0.39	0.55
Niedersachsen	de9	DE	0.21	0.22	0.33	0.48
Bremen	de5	DE	0.25	0.26	0.35	0.57
Nordrhein-Westfalen	dea	DE	0.25	0.27	0.37	0.46
Hessen	de7	DE	0.23	0.23	0.37	0.53
Rheinland-Pfalz + Saarland	deb+dec	DE	0.23	0.24	0.35	0.49
Baden-Wuerttemberg	de1	DE	0.25	0.27	0.40	0.52
Bayern	de2	DE	0.24	0.25	0.37	0.46
North & Cumbria	ukc + ukd1	UK	0.41	0.34	0.42	0.54
Yorks & Humberside	uke	UK	0.36	0.29	0.36	0.42
North West	ukd-ukd1	UK	0.41	0.35	0.43	0.44
East Midlands	ukf	UK	0.36	0.31	0.38	0.40
West Midlands	ukg	UK	0.43	0.35	0.45	0.49
East Anglia	ukh1	UK	0.36	0.31	0.39	0.48
Greater London	uki	UK	0.37	0.31	0.37	0.34
South East exc London	ukj+ukh2+ukh3	UK	0.46	0.38	0.50	0.52
South West	ukk	UK	0.42	0.35	0.44	0.51
Wales	ukl	UK	0.42	0.33	0.44	0.53
Scotland	ukm	UK	0.38	0.31	0.41	0.51
Nord Ovest	itc	IT	0.32	0.29	0.37	0.45
Nord Est	itd	IT	0.30	0.28	0.36	0.45
Centro (IT)	ite	IT	0.26	0.23	0.31	0.40
Sud (IT)	itf	IT	0.27	0.24	0.32	0.39
Isole (IT)	itg	IT	0.32	0.26	0.30	0.38
Île de France	fr1	FR	0.32	0.33	0.43	0.53
Bassin Parisien	fr2	FR	0.27	0.28	0.36	0.43
Nord - Pas-de-Calais	fr3	FR	0.26	0.27	0.35	0.43
Est	fr4	FR	0.29	0.30	0.40	0.48
Ouest	fr5	FR	0.27	0.29	0.37	0.42
Sud-Ouest	fr6	FR	0.28	0.29	0.39	0.45
Centre-Est	fr7	FR	0.26	0.28	0.36	0.44
Méditerranée	fr8	FR	0.28	0.29	0.35	0.44
Flandern	be2	BE	0.47	0.45	0.64	0.89
Wallonia	be3	BE	0.42	0.38	0.53	0.75
Brussel	be1	BE	0.44	0.42	0.50	0.85
Noroeste	es1	ES			0.21	0.27
Noreste	es2	ES			0.23	0.28
Comunidad de Madrid	es3	ES			0.22	0.28
Centro (ES)	es4	ES			0.20	0.25
Este	es5	ES			0.21	0.26
Sur	es6	ES			0.19	0.25
Canarias (ES)	es7	ES			0.21	0.27
Voreia Ellada	gr1	GR			0.21	0.29
Kentriki Ellada	gr2	GR			0.26	0.32
Attiki	gr3	GR			0.23	0.34
Nisia Aigaiou, Kriti	gr4	GR			0.20	0.28
Finland	Fi	FI			0.52	0.59
Denmark	Den	DEN			0.60	0.67
Luxembourg	Lux	LU				0.50
Ireland	Ir	IE			0.53	0.83
Austria Ost	Aus1	AT			0.35	0.42
Austria Sd	Aus2	AT			0.35	0.44
Austria West	Aus3	AT			0.37	0.43
Sweden	Swe	SE			0.57	0.75
Mecklenburg-Vorpommern	de8	DE			0.31	0.36
Brandenburg	de4	DE			0.33	0.42
Sachsen-Anhalt	dee	DE			0.34	0.41
Thüringen	deg	DE			0.32	0.40
Sachsen	ded	DE			0.36	0.45

Table 7.4: Import Competition Data: IC

Name	NUTS	Country	1985	1990	1995	2000
Berlin (west)	de3	DE	0.56	0.74	0.36	0.74
Schleswig-Holstein	def	DE	0.48	0.56	0.19	0.74
Hamburg	de6	DE	0.74	0.67	0.33	0.80
Niedersachsen	de9	DE	0.53	0.50	0.19	0.80
Bremen	de5	DE	0.34	0.62	0.14	0.76
Nordrhein-Westfalen	dea	DE	0.54	0.63	0.24	0.86
Hessen	de7	DE	0.44	0.44	0.25	0.87
Rheinland-Pfalz + Saarland	deb+dec	DE	0.44	0.41	0.14	0.87
Baden-Wuerttemberg	de1	DE	0.42	0.55	0.30	0.88
Bayern	de2	DE	0.43	0.53	0.32	0.90
North & Cumbria	ukc + ukd1	UK	0.71	0.03	0.45	0.22
Yorks & Humberside	uke	UK	0.61	0.05	0.35	0.23
North West	ukd-ukd1	UK	0.76	0.03	0.41	0.26
East Midlands	ukf	UK	0.73	0.05	0.35	0.30
West Midlands	ukg	UK	0.65	0.08	0.51	0.20
East Anglia	ukh1	UK	0.64	0.03	0.31	0.19
Greater London	uki	UK	0.75	0.01	0.35	0.23
South East exc London	ukj+ukh2+ukh3	UK	0.80	0.03	0.51	0.25
South West	ukk	UK	0.73	0.06	0.46	0.18
Wales	ukl	UK	0.63	0.04	0.55	0.28
Scotland	ukm	UK	0.66	0.03	0.39	0.32
Nord Ovest	itc	IT	0.43	0.17	0.93	0.69
Nord Est	itd	IT	0.45	0.19	0.90	0.69
Centro (IT)	ite	IT	0.59	0.29	0.90	0.67
Sud (IT)	itf	IT	0.45	0.26	0.87	0.58
Isole (IT)	itg	IT	0.29	0.12	0.81	0.45
Île de France	fr1	FR	0.69	0.41	0.28	0.78
Bassin Parisien	fr2	FR	0.55	0.42	0.21	0.78
Nord - Pas-de-Calais	fr3	FR	0.39	0.40	0.26	0.75
Est	fr4	FR	0.51	0.41	0.21	0.73
Ouest	fr5	FR	0.58	0.45	0.24	0.65
Sud-Ouest	fr6	FR	0.50	0.43	0.25	0.71
Centre-Est	fr7	FR	0.56	0.52	0.24	0.85
Méditerranée	fr8	FR	0.59	0.36	0.21	0.73
Flandern	be2	BE			0.50	0.59
Wallonia	be3	BE			0.34	0.44
Brussel	be1	BE			0.32	0.51
Noroeste	es1	ES			0.81	0.87
Noreste	es2	ES			0.75	0.74
Comunidad de Madrid	es3	ES			0.84	0.71
Centro (ES)	es4	ES			0.87	0.87
Este	es5	ES			0.86	0.79
Sur	es6	ES			0.87	0.87
Canarias (ES)	es7	ES			0.81	0.87
Voreia Ellada	gr1	GR			0.58	0.61
Kentriki Ellada	gr2	GR			0.47	0.50
Attiki	gr3	GR			0.33	0.51
Nisia Aigaiou, Kriti	gr4	GR			0.52	0.49
Finland	Fi	FI		0.35	0.14	0.45
Denmark	Den	DEN			0.19	0.47
Luxembourg	Lux	LU				
Ireland	Ir	IE	0.17	0.28	0.15	0.66
Austria Ost	Aus1	AT			0.09	0.46
Austria Sd	Aus2	AT			0.12	0.40
Austria West	Aus3	AT			0.11	0.36
Sweden	Swe	SE		0.33	0.16	0.37
Mecklenburg-Vorpommern	de8	DE			0.08	0.63
Brandenburg	de4	DE			0.12	0.79
Sachsen-Anhalt	dee	DE			0.06	0.77
Thüringen	deg	DE			0.22	0.82
Sachsen	ded	DE			0.21	0.82

Table 7.5: Import Penetration Ratio Data: IMPEX

Name	NUTS	Country	1985	1990	1995	2000
Berlin (west)	de3	DE	0.20	0.14	0.16	0.25
Schleswig-Holstein	def	DE	0.11	0.12	0.11	0.21
Hamburg	de6	DE	0.21	0.18	0.17	0.22
Niedersachsen	de9	DE	0.12	0.12	0.13	0.20
Bremen	de5	DE	0.16	0.16	0.15	0.24
Nordrhein-Westfalen	dea	DE	0.15	0.15	0.15	0.23
Hessen	de7	DE	0.13	0.14	0.17	0.23
Rheinland-Pfalz + Saarland	deb+dec	DE	0.12	0.12	0.13	0.17
Baden-Wuerttemberg	de1	DE	0.16	0.16	0.20	0.25
Bayern	de2	DE	0.18	0.18	0.19	0.29
North & Cumbria	ukc + ukd1	UK	0.21	0.22	0.24	0.30
Yorks & Humberside	uke	UK	0.21	0.20	0.26	0.29
North West	ukd-ukd1	UK	0.23	0.24	0.26	0.27
East Midlands	ukf	UK	0.22	0.23	0.28	0.30
West Midlands	ukg	UK	0.28	0.26	0.30	0.34
East Anglia	ukh1	UK	0.21	0.20	0.25	0.33
Greater London	uki	UK	0.21	0.17	0.18	0.20
South East exc London	ukj+ukh2+ukh3	UK	0.23	0.21	0.27	0.30
South West	ukk	UK	0.21	0.21	0.25	0.30
Wales	ukl	UK	0.26	0.23	0.27	0.34
Scotland	ukm	UK	0.22	0.19	0.25	0.29
Nord Ovest	itc	IT	0.15	0.13	0.16	0.21
Nord Est	itd	IT	0.10	0.10	0.14	0.17
Centro (IT)	ite	IT	0.11	0.10	0.14	0.18
Sud (IT)	itf	IT	0.10	0.10	0.13	0.16
Isole (IT)	itg	IT	0.14	0.11	0.14	0.15
Île de France	fr1	FR	0.12	0.13	0.17	0.26
Bassin Parisien	fr2	FR	0.14	0.16	0.19	0.27
Nord - Pas-de-Calais	fr3	FR	0.14	0.16	0.17	0.26
Est	fr4	FR	0.13	0.16	0.17	0.28
Ouest	fr5	FR	0.14	0.16	0.17	0.24
Sud-Ouest	fr6	FR	0.10	0.13	0.15	0.21
Centre-Est	fr7	FR	0.13	0.14	0.18	0.26
Méditerranée	fr8	FR	0.10	0.10	0.12	0.17
Flandern	be2	BE	0.28	0.24	0.31	0.41
Wallonia	be3	BE	0.25	0.24	0.24	0.35
Brussel	be1	BE	0.26	0.22	0.26	0.35
Noroeste	es1	ES			0.11	0.16
Noreste	es2	ES			0.14	0.19
Comunidad de Madrid	es3	ES			0.13	0.18
Centro (ES)	es4	ES			0.11	0.16
Este	es5	ES			0.14	0.20
Sur	es6	ES			0.11	0.15
Canarias (ES)	es7	ES			0.36	0.46
Voreia Ellada	gr1	GR			0.16	0.23
Kentriki Ellada	gr2	GR			0.13	0.24
Attiki	gr3	GR			0.25	0.36
Nisia Aigaiou, Kriti	gr4	GR			0.10	0.22
Finland	Fi	FI			0.18	0.21
Denmark	Den	DEN			0.19	0.21
Luxembourg	Lux	LU				
Ireland	Ir	IE			0.34	0.34
Austria Ost	Aus1	AT			0.12	0.18
Austria Sd	Aus2	AT			0.12	0.21
Austria West	Aus3	AT			0.12	0.20
Sweden	Swe	SE			0.17	0.22
Mecklenburg-Vorpommern	de8	DE			0.07	0.14
Brandenburg	de4	DE			0.08	0.14
Sachsen-Anhalt	dee	DE			0.11	0.16
Thüringen	deg	DE			0.12	0.23
Sachsen	ded	DE			0.11	0.21

Table 7.6: Offshoring Intensity Data: OFFSM

Name	NUTS	Country	1985	1990	1995	2000
Berlin (west)	de3	DE	0.18	0.18	0.21	0.26
Schleswig-Holstein	def	DE	0.15	0.16	0.20	0.25
Hamburg	de6	DE	0.18	0.18	0.22	0.29
Niedersachsen	de9	DE	0.14	0.15	0.20	0.25
Bremen	de5	DE	0.13	0.14	0.21	0.25
Nordrhein-Westfalen	dea	DE	0.16	0.17	0.22	0.27
Hessen	de7	DE	0.16	0.16	0.22	0.27
Rheinland-Pfalz + Saarland	deb+dec	DE	0.16	0.16	0.21	0.26
Baden-Wuerttemberg	de1	DE	0.17	0.17	0.22	0.26
Bayern	de2	DE	0.17	0.16	0.21	0.25
North & Cumbria	ukc + ukd1	UK	0.27	0.28	0.26	0.28
Yorks & Humberside	uke	UK	0.26	0.27	0.25	0.24
North West	ukd-ukd1	UK	0.28	0.29	0.26	0.25
East Midlands	ukf	UK	0.28	0.29	0.26	0.24
West Midlands	ukg	UK	0.25	0.28	0.26	0.27
East Anglia	ukh1	UK	0.25	0.26	0.24	0.26
Greater London	uki	UK	0.27	0.28	0.26	0.23
South East exc London	ukj+ukh2+ukh3	UK	0.27	0.29	0.27	0.28
South West	ukk	UK	0.26	0.28	0.25	0.27
Wales	ukl	UK	0.27	0.28	0.27	0.28
Scotland	ukm	UK	0.27	0.28	0.27	0.27
Nord Ovest	itc	IT	0.23	0.19	0.23	0.25
Nord Est	itd	IT	0.20	0.16	0.20	0.23
Centro (IT)	ite	IT	0.19	0.15	0.20	0.22
Sud (IT)	itf	IT	0.20	0.16	0.20	0.21
Isole (IT)	itg	IT	0.24	0.22	0.26	0.25
Île de France	fr1	FR	0.23	0.23	0.22	0.20
Bassin Parisien	fr2	FR	0.23	0.23	0.21	0.19
Nord - Pas-de-Calais	fr3	FR	0.23	0.23	0.21	0.19
Est	fr4	FR	0.22	0.23	0.22	0.19
Ouest	fr5	FR	0.21	0.21	0.20	0.17
Sud-Ouest	fr6	FR	0.22	0.22	0.21	0.18
Centre-Est	fr7	FR	0.25	0.25	0.22	0.20
Méditerranée	fr8	FR	0.24	0.23	0.21	0.20
Flandern	be2	BE			0.47	0.49
Wallonia	be3	BE			0.45	0.47
Brussel	be1	BE			0.48	0.50
Noroeste	es1	ES			0.23	0.28
Noreste	es2	ES			0.25	0.30
Comunidad de Madrid	es3	ES			0.26	0.31
Centro (ES)	es4	ES			0.21	0.26
Este	es5	ES			0.23	0.28
Sur	es6	ES			0.20	0.25
Canarias (ES)	es7	ES			0.23	0.28
Voreia Ellada	gr1	GR			0.21	0.23
Kentriki Ellada	gr2	GR			0.22	0.25
Attiki	gr3	GR			0.25	0.29
Nisia Aigaiou, Kriti	gr4	GR			0.21	0.24
Finland	Fi	FI			0.29	0.30
Denmark	Den	DEN			0.36	0.38
Luxembourg	Lux	LU			0.46	0.47
Ireland	Ir	IE				0.65
Austria Ost	Aus1	AT			0.38	0.43
Austria Sd	Aus2	AT			0.36	0.44
Austria West	Aus3	AT			0.37	0.43
Sweden	Swe	SE			0.33	0.35
Mecklenburg-Vorpommern	de8	DE			0.20	0.23
Brandenburg	de4	DE			0.22	0.25
Sachsen-Anhalt	dee	DE			0.21	0.25
Thüringen	deg	DE			0.20	0.25
Sachsen	ded	DE			0.22	0.26

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